Assessing Mental Health Status Among University Students: A Case Study of NUST

By

MUHAMMAD MOHSIN

(Registration No: 00000359909)

Department of Engineering

School of Interdisciplinary Engineering and Sciences (SINES)

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

(2024)

Assessing Mental Health Status Among University Students: A Case Study of NUST

By

Student Name: Muhammad Mohsin

(Registration No: 00000359909)

A thesis submitted to the National University of Sciences and Technology, Islamabad,

in partial fulfillment of the requirements for the degree of

Master of Science in

Computational Science & Engineering

Supervisor: Dr. ZARTASHA MUSTANSAR

Co Supervisor: Dr. ZAMIR HUSSAIN

School of Interdisciplinary Engineering and Sciences (SINES)

National University of Sciences & Technology (NUST)

Islamabad, Pakistan

Annex A to NUST Letter No
0972/102/Exams/Thesis Ce
dated 23 Dec 16.

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS/MPhil thesis written by Mr. Muhammad Mohsin Registration No. 359909 of SINES has been vetted by undersigned, found complete in all aspects as per NUST Statutes/Regulations, is free of plagiarism, errors, and mistakes and is accepted as partial fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature with stamp:

Dr. Zartasha Mustansar
HoD SINES
Tenured Associate Professor
SINES - NUST, Sector H-12
Islamabad

Name of Supervisor: Dr. Zartasha Mustansar.

Date: 19-01-2024.

Signature of HoD with stamp

Date: 19/01/2024

Countersign by

Signature (Dean/Principal)

Dr. Hammad M. Cheema
Principal & Dean
SINES - NUST, Sector H-12
Islamabad

Date: 24/01/24

DECLARATION

I MUHAMMAD MOHSIN hereby state that my MS thesis titled "Assessing Mental Health Status Among University Students: A Case Study of NUST" is my own work and has not been submitted previously by me for taking any degree from National University of Sciences and Technology, Islamabad or anywhere else in the country/ world.

At any time if my statement is found to be incorrect even after I graduate, the university has the right to withdraw my MS degree.

Name of Student: Muhammad Mohsin

Date: 17-01-2024

To my family, this thesis stands as a testament to the unwavering love, support, and guidance you have graciously bestowed upon me. Your sacrifices and unconditional love have been the guiding light through my academic journey. Your wisdom, encouragement, and belief in my abilities have been the cornerstone of my perseverance and success.

To my fellow students at the NUST, companionship and support that I have received at the NUST has been invaluable. You have been my source of endless motivation needed to complete this thesis desertion.

This accomplishment is not mine alone, but a reflection of our collective hopes, and aspirations. I dedicate this thesis to you, as a symbol of my eternal gratitude.

ACKNOWLEDGEMENTS

With the name of Allah, the most compassionate, the most merciful, I would like to begin by expressing my sincere appreciation to my Supervisor, Dr. Zartasha Mustansar, and Co-Supervisor, Dr. Zamir Hussain, whose invaluable assistance was instrumental in the completion of my master's thesis. I am highly indebted to all the students at the NUST, especially those who participated in my study. I extend my gratitude to my guidance committee members, Dr. M Tariq Saeed and Dr. Umar Asgher for the guidance and unwavering support throughout my thesis research work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

WHO	World Health Organization
APA	American Psychiatric Association
GHQ	General Health Questionnaire
K6 & K10	Kessler Psychological Distress Scales
GAD-7	General Anxiety Disorder Questionnaire
DASS	Depression, Anxiety, Stress Scale
AI & XAI	Artificial Intelligence & Explainable Artificial Intelligence
OR	Odds Ratio

ABSTRACT

University students globally face higher mental health issues as compared to the general population. Evidence underscores a spectrum of depression, with prevalence oscillating from 10% to a staggering 85%, culminating in a weighted mean prevalence of 30.6%. This alarming reality not only jeopardizes the academic performance of students but also casts a pervasive shadow on their holistic well-being.. While the discourse on the global stage is fervent, a persistent lacuna exists, demanding targeted studies, interventions, and a call for stakeholder engagement at the university level. . This study aims to assess the prevalence of anxiety, depression, and stress among students at the National University of Sciences & Technology (NUST) and to identify key factors contributing to these conditions. A second aim of this study is to develop an accessible information system for stakeholders to pinpoint and address key concerns for comprehensive mental health assessments and strategic interventions that resonate among the students in general. A cross-sectional study design was employed, utilizing the Depression, Anxiety, and Stress Scale-21 Items (DASS-21) to measure mental health conditions among 530 students. Binary logistic regression analysis was used to identify significant predictors of mental health issues. Machine learning techniques were used to reduce the number of items in DASS-21. Additionally, a Dash-based web application was developed for data visualization.

Descriptive statistics indicated that the majority participants (75.28%) were of age 18 to 25 whereas 56.23% were male. Findings indicate a high prevalence of extremely severe depression and anxiety, affecting 27.54% and 31.69% of students, respectively. Conversely, (36.41%) exhibited normal stress levels. Logistic regression analysis revealed that female students are more likely to report all three conditions stress, anxiety, and depression. Depression was also associated with age, financial concerns, and perceived social support. Anxiety correlated with the type of accommodation and social support. Stress was related to gender, educational level, and social support.

The Dash-based web application proved effective in visualizing complex data, facilitating better understanding and decision-making. This study fills the research gap by collection and assessment of university level data. The findings highlight an urgent need for university authorities to focus on the mental health of students to improve overall quality of life. The significant impact of depression and anxiety on academic performance warrants the inclusion of management strategies for these conditions in university orientations.

Keywords: DASS-21, mental health, binary logistic regression, Dash web application, sociodemographic factors, depression, anxiety, stress.

CHAPTER 1: INTRODUCTION

For a student transition to university life brings a plethora of changes. Where student gets to explore the world of academia but at the same time there are a lot of expectations from the student, sometimes this transition comes at the cost of mental health of the student. Mental health challenges among university students have become an increasingly pressing concern in recent years. The transition to university life can present a myriad of stressors, from adjusting to a new social environment to academic pressures, which can exacerbate or trigger existing mental health issues such as depression, stress, and anxiety [1] [2]. The World Health Organization (WHO) identifies mental health as an integral component of human health, stating that "there is no health without mental health" [3].

1.1. Background on mental health and prevalence among university students

The population of university students has a notable prevalence of mental health issues. Ibrahim et al.'s systematic review [4] highlights that psychological distress is highly prevalent among university students across the globe, with rates of diagnosed mental health conditions being higher within this demographic than in the general population. This is corroborated by the American College Health Association, which has reported that over 40% of college students felt depressed to the level where it was difficult to function, and over 60% felt overwhelming anxiety in the last year[5] .

Depression, anxiety, and stress are distinct yet interrelated psychological conditions that are particularly prevalent among university students due to the unique pressures of this life stage.

1.1.1. Depression

Depression in is often characterized by a persistent feeling of sadness, a lack of interest in previously enjoyed activities, and a pronounced reduction in energy and motivation. These symptoms can detrimentally affect academic performance, social interactions, and overall quality of life. The American Psychiatric Association (APA) [6] describes depression as despair or extreme sadness. It can interfere day-to-day activities and may cause physical symptoms such as weight loss or gain, pain, lack of energy, or sleeping pattern disruptions. Depression can lead to feeling of guilt or worthlessness. Extreme cases may have suicidal or death related thoughts.

1.1.2. Anxiety

Anxiety as defined by the APA an emotional state marked by tense sensations, anxious thoughts, and bodily changes like elevated blood pressure. Anxiety disorder sufferers typically experience intrusive thoughts or worries on a regular basis. They might steer clear of particular circumstances out of fear. Unlike fear, which is typically associated with spikes in autonomic arousal for fight-or-flight, anxiety is associated with tension and caution in anticipation of potential danger [6]. For students, this may manifest as test anxiety, social anxiety, or generalized anxiety about their future prospects, and problem is that it can lead to avoidance behaviors that interfere with effective coping strategies [7].

1.1.3. Stress

As per APA Stress is a normal reaction to everyday pressure situations, but it becomes unhealthy if it affects day-to-day functioning of the individual [6]. Stress among university students may be a response to pressures such as academic workload, financial burdens, and constant personal and professional life changes. In the academic environment, this can result in an overwhelming state, leading to burnout and other mental health challenges[8].

For university students, these conditions may not only be academic or clinical concerns; they are lived experiences that tangibly impact their capacity to learn, engage, and progress through their formative university years. The relationship between these mental health issues and the academic environment is complex, requiring a nuanced understanding to effectively address them[9].

1.2. Overview of the NUST

The National University of Sciences & Technology (NUST) in Pakistan represent broader trends observed among university students. As a leading institution in the region, NUST is home to a diverse student body of both national and international students facing unique challenges. NUST with its 7 campuses in 5 different cities and presence in all major provinces of Pakistan represents university students across the country. Multiple need-based scholarship and industry collaboration ensures an inclusive community of university students in Pakistan as shown in Figure 1.

Sociodemographic factors such as gender, age, socioeconomic status, and living arrangements for university students have been shown to influence mental health. Women have been found to be at a higher risk for anxiety and depression during their university years, whereas male undergraduate students are at a higher risk of suicide [9]. Additionally, the type of accommodation, whether on-campus or off-campus, can affect a student's mental health particularly depression due to varying degrees of social support and environmental stressors [10], [11].

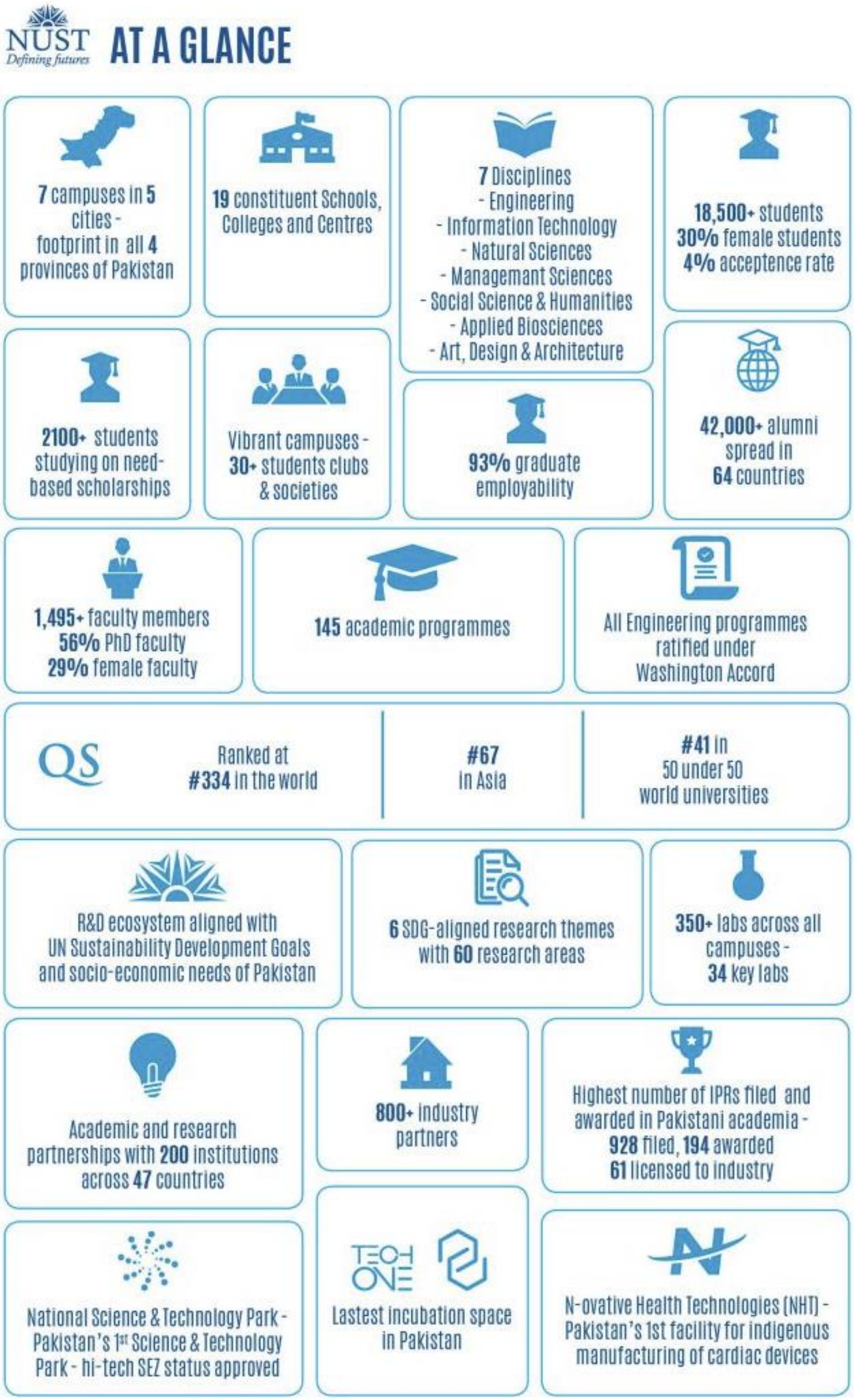

Figure 1.1: NUST at a glance.

1.3. Problem Statement

This research focuses on two core problem: firstly, to assess the prevalence mental health issues among university students, particularly in terms of depression, stress, and anxiety. This involves the use of the DASS-21 questionnaire to gauge the prevalence and intensity of these conditions among the student body. Secondly, there is no user-friendly dashboard as an information system for stakeholders to understand the extent of the mental health issues. This system will aid in the visualization and interpretation of the collected data, making it more accessible for stakeholders such as university administrators and mental health professionals [1].

Another problem statement developed through literature review and data collection process is that that length of the DASS-21 questionnaire can be a barrier to frequent and widespread use. This is backed by reduced attention span of modern-day university students with frequent internet usage [12].

1.4. Objectives of the Study

1.4.1. Assessing Prevalence of Depression, Anxiety, and Stress

The first goal is to determine how common anxiety, stress, and depression are among students of NUST. In order to obtain insight into the mental health status at the university, data collection is done by administrating the DASS-21 questionnaire to a representative sample of students. The goal is to understand the extent and severity of these conditions, providing a foundational basis for targeted interventions and support programs[10], [13], [14].

1.4.2. Development of a Dashboard

The second objective focuses on developing a dashboard as an information system for stakeholders. The purpose of this digital platform is to display and analyze the information gathered from the DASS-21 tests. It aims to provide university administrators, mental health professionals, and other stakeholders with actionable insights, facilitating informed decision-making. [15], [16].

1.4.3. Use of Machine Learning for Reduction in DASS-21 Questionnaire

The final objective involves the application of machine learning techniques to optimize the DASS-21 questionnaire to reduce the number of questions. The study seeks to streamline the assessment process, making it more efficient and less time-consuming for students. This is to be achieved while maintaining the questionnaire's diagnostic integrity while enhancing its practicality for regular use in the university settings. This innovation aims to facilitate more frequent mental health screenings, contributing to practical mental health care at NUST [17], [18].

CHAPTER 2: LITERATURE REVIEW

This chapter delves into the existing body of literature surrounding the key themes of our research: the prevalence of mental health issues among university students, the use of assessment tools other than the DASS-21, the development of information systems (dashboards) in public healthcare with a focus on mental health data, and the application of machine learning in psychological assessments. By examining these areas, we aim to establish a foundation for our study, highlighting its relevance and necessity.

2.1 Scope of the Review

Review will span several critical areas. Initially, we will explore studies focusing on the prevalence of depression, anxiety, and stress among university students, with a particular emphasis on research conducted in similar academic environments to NUST. This will include a discussion on the methodologies employed and the key findings.

Next, we will examine the literature on the mental health assessment questionnaires, their effectiveness, and use in various settings. The goal is to understand different tool's strengths and limitations in assessing mental health conditions.

Following this, we will review existing studies on information systems, specifically dashboards, used for visualizing mental health data. This part will focus on the impact of such systems on stakeholders' decision-making processes and their effectiveness in a university context.

Finally, we will explore the burgeoning field of machine learning in mental health assessments. This will include a review of studies that have successfully employed machine learning techniques to optimize assessment tools, drawing parallels and insights relevant to our objective of refining the DASS-21 questionnaire.

2.2 Prevalence of Mental Health Issues among Students

The prevalence of mental health issues in higher education settings has emerged as a significant concern worldwide. University students are uniquely vulnerable to psychological distress due to factors like academic pressures, life transitions, and social challenges. This section reviews various studies to understand the extent and nature of mental health problems, particularly depression, stress, and anxiety, among university students.

2.2.1 Global Perspective

Mental health issues have been highlighted by researcher across different geographical and cultural contexts. Consistently reporting high rates of mental health issues among university students. A multinational study involving 14 countries revealed that one in three university students reported experiencing at least one mental health disorder, with depression and anxiety being the most common. This underscores the global nature of this issue, indicating that mental health concerns among students are not confined to specific regions or cultures [19].

2.2.2 Pakistan-Specific Perspective

In Pakistan, the situation reflects the global trends but with some local distinctions. A systematic review and meta-analysis study that focused on depressive symptoms among Pakistani university students highlighted the significant prevalence of depressive condition. This comprehensive review, utilized a systematic search strategy across multiple databases, including PubMed and Google Scholar, to compile data on depressive symptoms among university students in Pakistan.

The study found a considerable prevalence rate of depressive symptoms, emphasizing the need for attention to mental health awareness in Pakistani educational settings [20].

2.3 Factors Contributing to Mental Health Issues

Whereas there can be various and unique factors affecting mental health of student across world. Several studies have attempted to identify common factors contributing to mental health issues in university students. A research form 2007 found that academic stress, financial concerns, and personal relationships were significant predictors of mental health problems [2].

A systematic review focusing on the mental health of college and university students in the UK, identified several critical factors related to metal health problems. The study found that experiences of childhood trauma, unique sexual orientation, and having autism are significantly associated with poor mental health in this demographic. Conversely, strong social networks and adaptability to the changes which inherent in higher education can serve as protective factors for students [21].

A study from 2008 found a negative correlation between mental health issues and academic satisfaction, suggesting that students suffering from mental health problems are more likely to experience difficulties in their academic work. This linkage further highlights the need for effective mental health interventions in university surroundings [22].

2.4 Comparison of Mental Health Assessment Tools:

The DASS-21 is among the widely recognized tools for assessing mental health issues. To understand its strengths and weaknesses, it's important to compare it with other similar tools such as: the General Health Questionnaire (GHQ), the Kessler Psychological Distress Scales (K6 and K10), the General Anxiety Disorder Questionnaire (GAD-7), and the WHO-5 Wellbeing Index.

2.4.1 General Health Questionnaire (GHQ):

GHQ was developed in the 1970s, the GHQ is a screening tool primarily used in non-psychiatric settings focusing on two domains, (difficulties in carrying out normal functioning and the emergence of any new or distressing circumstances). The GHQ is available is multiple versions. GHQ-12, a 12-item version focusing on emotional and social functioning is widely used and is available in multiple translations including Urdu. While it has shown good sensitivity and specificity, the GHQ-12 does not provide information about any particular disorders [23].

2.4.2 Kessler Psychological Distress Scales

The Kessler Psychological Distress Scales, K6 and K10, are screening tools developed to identify individuals at high risk for mental health problems. Both tools can be self-administered as well interviewer administered. As the name suggests K6 consists of six questions, while the K10 has ten. Both scales measure symptoms of nonspecific psychological distress. They were designed based on Item Response Theory models and have been validated in large-scale surveys. The K6 and K10 are particularly effective in detecting individuals in the higher percentile ranges of psychological distress in the population[24] [25].

2.4.3 Generalized Anxiety Disorder-7 (GAD-7)

GAD-7 is a self-report scale developed to identify probable cases of Generalized Anxiety Disorder (GAD) and evaluate its severity. It consists of seven items that assess the frequency of GAD symptoms over the past two weeks. Additionally, it can be used as a screening tool for PTSD, social anxiety, and panic attacks. The GAD-7 scale scores range from 0 to 21, with higher scores indicating greater anxiety severity. It has been validated for its reliability and effectiveness in both clinical practice and research. The tool is particularly useful for screening GAD and assessing its severity, making it a valuable resource in various healthcare settings [26].

2.4.4 WHO-5 Wellbeing Index

The WHO-5 Wellbeing Index is a self-report questionnaire designed to assess positive mental health and well-being. It consists of five items and has been found to be a valid and reliable measure of well-being across diverse populations. But because of its emphasis on wellbeing and good mental health, it might not be as good at spotting those who are struggling with mental health issues. This scale is validated for use across diverse populations and has been found to be a valid and reliable measure of well-being [27].

2.4.5 Depression, Anxiety, and Stress Scale (DASS)

The DASS-21 and DASS-42 are unique in their assessment of three dimensions of negative affect: depression, anxiety, and stress. The DASS-21 has been widely utilized in research settings and has shown good psychometric qualities. This makes it possible to evaluate mental health problems in a more thorough manner. The DASS-21 has demonstrated good psychometric properties and has been used extensively in research settings. However, its focus on negative affect may limit its usefulness in assessing positive mental health and well-being [28], [29].

Table 1 below summarize the differences between these five assessment tools. The DASS-21 was chosen for its unique ability to assess three different dimensions of mental health for university student population. This is particularly relevant for university students who often face a range of emotional challenges. Additionally, its shortness (as compared to the full DASS-42) makes it more feasible for use in a setting where time and resources may be limited. The tool's validation across diverse populations, including young adults in educational settings, further supports its applicability. Last but not least its free usage policy, requiring only proper citation, makes it accessible for academic research without the constraints of copyright issues [13], [30].

Table 2.1: Comparison of Mental Health Assessment Tools.

Tool Name	Delivered	Copyrighted	Population	Measure
GHQ (General Health Questionnaire)	Self-report questionnaire	Yes	Not validated in children	psychological distress
(K10 & 6) (Kessler Psychological Distress Scale)	Self-report questionnaire & Interviewer-administered	No	Validated in several ethnic minority groups, and in 21 languages.	Nonspecific
GAD-7 General anxiety disorder questionnaire	Self- report questionnaire	Copyright by Pfizer	Validated in populations only in populations of a few major countries.	Anxiety
The WHO-5 Wellbeing Index	Self- report questionnaire	No	Multiple translations do exist for over 30 languages. Validated for age over 9 years.	General Mental Wellbeing
(DASS-42 and 21) Depression, Anxiety, Stress Scales	Self- report questionnaire	No	Validated for people over the age of 17. Has been translated into 50+ languages including Urdu.	Depression Anxiety Stress

2.5 Information Systems for Mental Health:

2.5.1 Introduction to Dashboards in Healthcare:

Dashboards are important tools in visualizing and interpreting data within various sectors, including healthcare. Studies suggest that application of dashboards in managing mental health and demographic data, has shown potential in improving mental health services. Literature also suggests that the dashboards have played a key role in enabling timely and targeted adjustments to mental health service delivery[31].

The need for interactive tools like performance dashboards in healthcare improves decision-making and performance management. Dashboards are particularly useful with established Key Performance Indicators (KPIs), data sources and quality, integration with source systems[32].

2.5.2 Role of Dashboards in Mental Health Data

Dashboards play a major role in decision-making. Dashboards in mental health information systems allow users to understand key data in a simple yet actionable manner. Dashboard allow to switch between presentation formats and to adapt to different user characteristics and tasks. Dashboards effectively display complex datasets, aiding in the interpretation and decision making related mental health trends among university students[33]. Dashboards are proven to enable the monitoring of mental health indicators in real-time, allowing for prompt responses to emerging mental health issues [34]. Dashboards can facilitate individualized approaches in mental health care by presenting tailored data for each student, this approach help stakeholders to make decision for minority communities to individuals affected [35]

Dashboards in mental health interventions facilitate evidence-based decision-making by encouraging reliance on empirical evidence. They also play a pivotal role in policy formulation, as the insights garnered from these dashboards ensure that mental health strategies are data-driven. Moreover, dashboards significantly contribute to stakeholder engagement, promoting the involvement of various parties and fostering a collaborative approach to mental health care. This multidimensional utility underscores the impact of dashboards in the mental health sector [16], [36]

Despite the benefits, dashboards in mental health raise concerns about data privacy and accurate interpretation of mental health data. It is essential to maintain confidentiality and ensure accurate data representation to prevent misinterpretations [37].

2.6 Streamlining DASS-21: Approaches to Item Reduction in Mental Health Assessment

The need for efficient mental health assessment tools is reflected in several assessment tools discussed so far with 5 or 7 items. Original DASS is a tool with 42 items. The DASS, with 42 items, was later compressed into DASS-21, a shorter version maintaining the tripartite structure of depression, anxiety, and stress. Despite its briefness, DASS-21 still is a long questionnaire requiring undivided attention of participant filling the questionnaire and there is definite need for a shorter yet effective questionnaire.

There have been studies which investigated into reducing DASS-21's length while retaining its diagnostic integrity. Using techniques like Item Response Theory (IRT) and Confirmatory Factor Analysis (CFA), researchers have identified the most informative and discriminative items. The goal is to distill the essence of the DASS-21 into an even more concise form without compromising its psychometric properties[17], [39].

Studies show the possibility of a 12-item version, termed Mini-DASS, which retains high reliability and validity. This condensed version not only ensures faster administration but also reduces respondent fatigue, enhancing the potential for accurate self-reporting. Such reductions are particularly significant in large-scale surveys or populations with limited time or concentration resources. The Mini-DASS demonstrates psychometric robustness equivalent to DASS-21, affirmed by its invariant structure across different demographics and cultural contexts. This universal applicability is crucial, considering the diverse settings in which mental health assessments are conducted [39], [40].

While the abbreviated versions like Mini-DASS is a significant step forward, ongoing research is needed to explore their applicability in varied clinical and non-clinical contexts. Future studies should also examine the impact of further item reduction on the diagnostic accuracy of the scale.

CHAPTER 3: METHODS

3.1 Sample Size and Inclusion criterion:

The target population for our study comprised students currently enrolled at the NUST. We used a confidence level of 95%, a margin of error of 5%, and an estimated population size of 18,500 students. To calculate the sample size necessary for our study, we applied Cochran's sample size formula, which is designed for categorical data[41] :

$$n = (Z^2 * p * (1 - p)) / e^2$$

Where:

- n is the sample size
- Z is the Z-score corresponding to the desired confidence level (1.96 for 95% confidence)
- p is the estimated proportion of the attribute present in the population (0.5 for maximum variability)
- e is the desired level of precision or margin of error (0.05 for a 5% margin)

Note: Formula assumes infinite population.

Inserting the values into the formula, we get:

$$n = (1.96^2 * 0.5 * (1 - 0.5)) / 0.05^2$$

By calculating the above, we determined that the minimum sample size required for our study would be approximately 384 respondents.

A total of 651 respondents participated in the study which exceeds the calculated minimum sample size, thus ensuring the reliability of the survey results. However, after a thorough review of the respondent criteria, only 530 participants were included in the final analysis. Only those participants who were currently enrolled as students at NUST were included in the analysis. Exclusions were made based on the status of the respondents: those who did not consent (no further data was collected), those who were not currently enrolled students, as well as faculty and alumni, were omitted from the study. Researchers who designed the survey were excluded from the study. Additionally, participants of pilot study or students from School where pilot study was conducted were excluded from the final analysis.

3.2 Ethical Considerations:

The online questionnaire commenced with an introductory statement outlining the purpose of the research, the voluntary nature of participation, the anonymity of the responses. It was informed to the participants that they have right to withdraw from the study at any point without any negative consequences.

Participants were informed that the DASS-21 is a self-report tool and should not be used a substitute for a clinical diagnosis. They were advised to seek professional help or contact their general physician for a referral if they were experiencing significant problems. This safety measure was implemented to guarantee that respondents were cognizant of the survey's constraints and the significance of seeking expert mental health services.

Individuals were required to actively consent by responding to the initial survey question: "I consent to participate in this research." This approach ensured that all participants were willing to be a part of the study. For any participant who did not consent, Google form ended there. The participants' confidentiality was maintained throughout the analysis and reporting stages. Data were stored securely and only accessible to the research team members.

3.3 Survey Development:

The survey consisted of two parts a. Generalized demographic questionnaire and b. DASS-21 questionnaire [42] [43]. The survey aimed to provide insights into the prevalence and severity of anxiety, depression, and stress among the target demographic. This strategy was based on the earlier research's identification of the need to comprehend these mental health issues along with several demographic factors in a university context [14].

The DASS-21 was the main component of the questionnaire. The DASS-21 is a well-established instrument in psychological assessment which offers a concise yet comprehensive measure of the three constructs that are depression, anxiety, stress [42]. Its inclusion was based on its proven reliability and validity in academic settings especially similar to target population and its validity for Urdu translation [43], [44]. DASS-21 part of the survey was designed in both Urdu & English languages.

The survey also included demographic questions to ascertain correlations between mental health status and factors such as age, gender, educational level, and living arrangements, aligning with methodologies used in similar studies [45][46].

3.4 Data Collection:

Prior to full deployment at the university level, the survey underwent a pilot testing at the School of Interdisciplinary Engineering & Sciences (SINES), NUST from 7th to 13th December 2022. This preliminary phase was conducted for assessing the clarity and relevance of the survey items within the intended population. The feedback obtained from initial phase informed necessary modifications, enhancing the survey's effectiveness for the subsequent deployment [47], [48].

Following the initial pilot testing phase, data collection at the university level was conducted using a self-administered questionnaire disseminated through online Google Forms from 21st to 28th December 2022. To ensure broader reach and minimize the potential for selection bias, the questionnaire was distributed employing a multifaceted approach: electronically via the university's official email system; physically through strategically placed posters with QR codes on the notice boards within principal buildings, including academic schools, the cafeteria, and libraries; and digitally via the social media platforms. This heterogeneous distribution methodology was purposefully employed to mitigate any bias that might arise from a singular mode of data dissemination[49] .

3.5 Statistical Analysis

Survey data collected via Google Forms was systematically stored in Microsoft Excel and subjected to analysis through the Python programming language. A data cleansing procedure was undertaken, addressing missing values, anomalies, and confirming data types, to ensure the data's suitability for analysis. Descriptive statistics were computed to explain the fundamental characteristics of the dataset. Additionally, the distribution of respondents' scores across the subscales of the DASS-21 spanning normal to extremely severe was examined.

In exploring the determinants of psychological distress—specifically depression, anxiety, and stress—binary logistic regression was employed. The DASS-21 subscale scores were dichotomized into 'non-symptomatic' for those within the normal range and 'symptomatic' for scores within mild to extremely severe ranges. Consequently, three distinct binary logistic regression models were constructed, corresponding to each DASS-21 subscale. The Wald test was utilized to deduce the significance of predictors, with the Odds Ratio (OR) quantifying the strength of association. A threshold of $p < 0.05$ was established for statistical significance.

The potential issue of multicollinearity amongst predictors was evaluated via the Variance Inflation Factor (VIF), ensuring the independence of variables. The goodness of fit of logistic regression models was evaluated by computing Cox-Snell and Nagelkerke pseudo-R-squared values alongside log-likelihood ratios, providing a composite view of the models' capabilities and their compatibility with the empirical data.

3.6 Machine Learning Approach for Reduction in DASS-21 items

To optimize mental health assessments, we further explored a novel approach of utilizing machine learning techniques to reduce the number of items in DASS-21 questionnaire. The rationale behind this approach is to reduce the time required to complete the assessment while maintaining its diagnostic integrity, thereby making it more accessible and less burdensome for participants. Techniques such as Feature Importance and correlation analysis were used to identify the most important questions among 21 items.

Dataset was pre-processed before the statistical analysis and later data was divided into three major sections:

- Demographic question
- DASS-21 questions
- Target feature (Depression, Anxiety, and Stress Scores)

Next step was the selection of most important features from the DASS-21 questionnaire. This selection was guided by a combination of two techniques feature importance and correlation analysis, where the relationship between individual DASS-21 items and the overall scores for Depression, Anxiety, and Stress was examined. The correlation analysis was visualized through heatmaps, providing an intuitive understanding of the interrelationships among variables.

1. Feature Importance:

Feature importance is a metric to calculate the relative significance of each input feature in the prediction outcomes of a machine learning model. This concept is instrumental in enhancing the interpretability of complex models, guiding feature engineering. The scores in this case represents the "importance" of each item in DASS-21. Higher score represents higher impact of an item on model in predicting the depression, anxiety, and stress scores.

2. Correlation analysis

Correlation analysis is a statistical method that is used to determine the strength (value) and direction (positive or negative) of the relationship between two variables. In our case, correlation analysis was employed to examine the relationships between items of the DASS-21 questionnaire and the respective scores for depression, anxiety, and stress. A fourth feature was created to measure average correlation of each item with respect to each depression, anxiety, and stress scores.

After feature importance and average correlation calculation, a new feature was created namely average metric that reflects the overall importance of each item included in DASS-21. Top 12 items were selected with highest average metric value to be used in further prediction and evaluation.

Later, we employed five different regression models, to predict depression, anxiety, and stress score based on 12-item. The models included:

- Linear Regression
- Decision Tree
- Gradient Boosting
- Random Forest
- Support Vector Regression

The training process involved feeding these models with a subset of the dataset with a 80/20 split for train and test respectively to learn the patterns and relationships between the questionnaire responses and the mental health scores.

After model training in our machine learning pipeline, we employed GridSearchCV, a method for hyperparameter tuning, to optimize several regression models. Using GridSearchCV, we systematically explored a hyperparameter values for models including Decision Tree, Random Forest, Gradient Boosting, and Support Vector Regression. Parameters like max_depth, min_samples_split, and n_estimators were varied. Linear Regression was also included, though it required no hyperparameter tuning.

Lastly, each model was trained and hyper tuned on a designated training dataset and then made predictions on a separate testing dataset. This approach ensures that the evaluation reflects the model's performance on previously unseen data, a key indicator of its ability to generalize. For model evaluation we used following metrics:

Mean Absolute Error (MAE): This metric claculate the average magnitude (absolute) of errors between the predicted and actual values, providing a straightforward interpretation of prediction accuracy.

Mean Squared Error (MSE): MSE measures the squared difference between actual and predicted value, heavily penalizing larger errors. This metric is sensitive to the scale of the data and outliers.

Root Mean Squared Error (RMSE): As the name suggest square root of MSE, RMSE is particularly useful as it brings the error metric back to the scale of the target variable.

R-squared (R2): R-squared, also known as the coefficient of determination, quantifies the proportion of the variance in the dependent variable (y) that can be explained by the independent variables (X) in a regression model. It is a measure of how well the model captures the variability of the data.

These metrics provided insights into various aspects of the models' performance, such as accuracy, error magnitude, and the proportion of variance in the dependent variable that is predictable from the independent variables.

3.7 Dashboard Development

The dashboard was developed using Python, with an emphasis on the Dash framework, a decision informed by its integration with Plotly for creating interactive data visualizations. Low code nature of Dash allows for quick prototyping. Dashboard was intended to display most important information with an interactive yet simple design for ease of understanding. This approach was observed as trends in healthcare technology where dashboards are increasingly utilized to synthesize and visualize large quantities of data, aiding in clinical and strategic decision-making [50].

The interactive dashboard created using Plotly enable a multilayered exploration of the data, consistent with the role of dashboards in providing awareness, trend analysis, and comparative insights in a simplified interface [51]. Data from student surveys was categorized using a custom Python function to assess mental health status. This method of data representation and categorization allows for effective communication of mental health status relevant to sociodemographic variables[15].

The dashboard's interactivity is designed to facilitate analysis and stakeholder engagement [52]. This allows for a dynamic exploration of the mental health landscape, offering stakeholders the ability to filter and dissect data across various variables.

CHAPTER 4: RESULTS

4.1 Participant's characteristics

Table 4.1 explains the demographic, socioeconomic attributes of the students. An examination of the demographic data illustrates that a majority of the participants were male (56.22%), resided in university campus hostels (49.81%), and were predominantly aged between 18-24 years (75.28%). The respondents reported having completed intermediate level of education (±12 years) (42.26%), identified with a middle-class socioeconomic status (57.54%), and a substantial proportion perceived educational expenses as a financial burden on their families (35.28%). The representation from the province of Punjab was significant (58.11%), with most participants having a Normal Body Mass Index (BMI) (61.32%) and considering their social network to be highly supportive (39.05%).

Table 4.1: Descriptive statistics of the study population

Variable		N	%
Gender			
	Male	298	56.22
	Female	232	43.77
Where do you live?			
	Hostel (inside the campus)	264	49.81
	Home	188	35.47
	Hostel (Outside the campus)	64	12.07
	Other	14	2.64
Highest Education Level Completed?			
	Intermediate	224	42.26
	Undergraduate	223	42.07
	Postgraduate	83	15.66
Socioeconomic status			
	Middle class	305	57.54

	Upper middle class	144	27.16
	Lower middle class	63	11.88
	Lower class	10	1.88
	Upper class	8	1.50
Your educational expenses are a financial burden on your family?			
	Yes	187	35.28
	No	163	30.75
	Partially	137	25.84
	Not sure	43	8.11
Marital Status			
	Single	495	93.39
	Married	30	5.66
	Other	5	0.94
How supportive do you think is your social circle (family and close friends):			
	Very supportive	207	39.05
	Somewhat supportive	158	29.81
	Extremely supportive	95	17.92
	A little bit supportive	57	10.75
	Not at all supportive	13	2.45
How would you rate your Body Mass Index (BMI):			
	Normal	325	61.32
	Overweight	109	20.56
	Underweight	87	16.41
	Obese	9	1.69
Your province:			
	Punjab	308	58.11
	Islamabad Capital Territory	77	14.52
	Khyber Pakhtunkhwa	66	12.45
	Sindh	52	9.81
	Other	27	5.09
Age			
	18-24	399	75.28
	25-30	117	22.07
	31-36	14	2.64

4.2 Prevalence of Mental Health Conditions

Table 4.2 displays the classification of respondents across the five designated categories (normal, mild, moderate, severe, and extremely severe) of mental health concerns, as quantified by the 21-item DASS scale. Of the 530 students surveyed, 139 (26.22%), 146 (27.54%), and 193 (36.41%) were categorized as asymptomatic/Normal for depression, anxiety, and stress, respectively. Conversely, the incidence of extremely severe levels of depression, anxiety, and stress was noted in 146 (27.54%), 168 (31.69%), and 65 (12.26%) participants, respectively.

The table 4.2 reveals the distribution across various mental health states, offering a critical insight into the psychological well-being of the university student population. These findings provide a foundation for subsequent analyses and discussions regarding the mental health interventions required at the institutional level.

Table 4.2 Prevalence and severity of depression, anxiety, and stress among the study participants

	N	%	N	%	N	%
	Depression		Anxiety		Stress	
Normal	139	26.22	146	27.54	193	36.41
Mild	63	11.88	45	8.49	75	14.15
Moderate	122	23.01	110	20.75	120	22.64
Severe	60	11.32	61	11.50	77	14.52
Extremely Severe	146	27.54	168	31.69	65	12.26

4.3 Logistic Regression

The logistic regression analysis identified several significant predictors of depression. Table 4.3 shows that being female significantly increased the likelihood of depression (OR = 2.12) compared to males. Age groups 18-24 (OR = 4.99) were at a higher risk compared to the reference group of 31-36 years. Students living inside campus hostels had a non-significant increase in the odds of depression compared to those living at home. Educational background and socioeconomic status, while varied, did not show significant effects when compared to postgraduate education and middle-class status, respectively. Perception of educational expenses as a financial burden (Yes) significantly increased the odds of depression (OR = 1.87). The level of social support was found to be a robust predictor, with ‘a little bit supportive' (OR = 5.88) and 'somewhat supportive' (OR = 2.89) environments increasing the odds of depression compared to very supportive environments.

Table 4.3: Determinants of depression as identified with binary logistic regression.

	Odds Ratio	Wald	P-value	CI lower	CI upper
Depression					
Female	2.123	10.230	**0.001**	1.338	3.367
Reference: Gender (Male)					
18-24	4.994	4.522	**0.033**	1.134	21.985
25-30	3.318	2.779	0.095	0.810	13.596
Reference: Age (31-36)					
Hostel inside campus	1.312	1.033	0.309	0.777	2.2157
Hostel outside campus	1.230	0.280	0.596	0.571	2.650
Reference: Accommodation (Home)					
Intermediate	1.263	0.377	0.539	0.599	2.662
Undergraduate	1.170	0.229	0.631	0.614	2.228
Reference: Education (Postgraduate)					
Lower class	0.464	0.999	0.317	0.103	2.086
Lower middle class	1.099	0.069	0.791	0.542	2.232
Upper class	1.173	0.033	0.854	0.213	6.454
Upper middle class	1.150	0.277	0.598	0.682	1.941
Reference: Socioeconomic Status (Middle class)					
Not sure	1.039	0.009	0.924	0.467	2.312
Partially	0.947	0.037	0.847	0.548	1.636
Yes	1.869	4.554	**0.032**	1.052	3.322

Reference: Education as financial burden (No)					
Married	1.399	0.401	0.526	0.494	3.959
Other	0.623	0.228	0.632	0.089	4.337
Reference: Marital Status (Single)					
A little bit supportive	5.875	13.296	**<0.001**	2.268	15.219
Extremely supportive	1.078	0.0743	0.785	0.626	1.856
Not at all supportive	6.967	3.127	0.076	0.810	59.915
Somewhat supportive	2.886	14.736	**<0.001**	1.679	4.958
Reference: Social Circle Support (Very supportive)					
Obese	0.948	0.003	0.953	0.161	5.554
Overweight	1.256	0.632	0.426	0.716	2.202
Underweight	1.433	1.236	0.266	0.759	2.703
Reference: Body Mass Index (Normal)					
Islamabad Capital Territory	1.431	0.641	0.423	0.595	3.441
Punjab	1.280	0.592	0.441	0.682	2.400
Sindh	1.173	0.135	0.713	0.499	2.756
Other	1.584	0.543	0.460	0.465	5.392
Reference: Province (Khyber Pakhtunkhwa)					

Table 4.4 suggests that gender remained a significant determinant for anxiety, with females having higher odds than males (OR = 3.38). Age did not significantly influence anxiety levels. Living in hostels outside the campus was associated with increased odds of anxiety (OR = 3.28). Financial perceptions and socioeconomic status did not present as significant determinants. Students from Sindh showed significantly lower odds of anxiety (OR = 0.41) compared to the reference province Khyber Pakhtunkhwa. However, a ‘little bit supportive’ social environment was associated with a significant increase in the odds of anxiety (OR = 5.31) as compared to reference category ‘Very supportive’.

Table 4.4: Determinants of anxiety as identified with binary logistic regression.

	Odds Ratio	Wald	P-value	CI lower	CI upper

Anxiety					
Female	3.378	24.524	**<0.001**	2.086	5.469
Reference: Male					
18-24	1.087	0.011	0.916	0.229	5.161
25-30	0.486	0.910	0.339	0.110	2.137
Reference: Age (31-36)					
Hostel inside campus	1.474	2.133	0.144	0.875	2.484
Hostel outside campus	3.278	7.140	**0.007**	1.372	7.833
Reference: Accommodation Home					
Intermediate	1.048	0.015	0.901	0.491	2.238
Undergraduate	1.177	0.237	0.625	0.609	2.275
Reference: Education (Postgraduate)					
Lower class	1.312	0.093	0.760	0.228	7.528
Lower middle class	1.061	0.029	0.863	0.535	2.104
Upper class	0.749	0.128	0.719	0.155	3.606
Upper middle class	0.981	0.004	0.945	0.579	1.664
Reference: Socioeconomic Status (Middle class)					
Not sure	1.209	0.195	0.658	0.521	2.804
Partially	0.989	0.001	0.971	0.568	1.722
Yes	1.485	1.842	0.174	0.839	2.628
Reference: Education as Financial burden (No)					
Married	1.254	0.195	0.658	0.459	3.420
other	0.114	3.170	0.074	0.010	1.243
Reference: Marital Status (Single)					
A little bit supportive	5.309	11.336	**<0.001**	2.009	14.032
Extremely supportive	0.858	0.278	0.597	0.487	1.512
Not at all supportive	4.456	1.863	0.172	0.521	38.105
Somewhat supportive	1.494	2.375	0.123	0.896	2.490
Reference: Social Circle Support (Very supportive)					
Obese	0.384	1.222	0.268	0.070	2.092
Overweight	1.518	1.976	0.159	0.848	2.717
Underweight	1.171	0.253	0.614	0.632	2.169
Reference: Body Mass Index (Normal)					
Islamabad Capital Territory	0.695	0.638	0.424	0.285	1.694
Punjab	0.953	0.019	0.888	0.489	1.857
Sindh	0.410	4.128	**0.042**	0.174	0.968
Other	0.807	0.128	0.719	0.252	2.588
Reference: Province (Khyber Pakhtunkhwa)					

Table 4.5 suggests that being gender is significant determinant for stress as well with female having higher odds (OR = 2.48) of having stress as compared to reference male. Age and living arrangements did not show a significant impact. Education is a strong determinant of stress with students who have completed intermediate education and undergraduate level having odds as 2.16 and 1.89 respectively, compared to students who have completed postgraduate education. 'A little bit supportive' social environments significantly increased the odds of stress (OR = 5.58), and those with 'not at all supportive' environments faced the highest odds (OR = 8.28) as compared to those with very supportive social circle.

Table 4.5: Determinants of stress as identified with binary logistic regression.

	Odds Ratio	Wald	P-value	CI lower	CI upper
Stress					
Female	2.484	18.065	**<0.001**	1.633	3.780
Reference : Male					
18-24	0.743	0.158	0.690	0.172	3.200
25-30	1.131	0.029	0.863	0.277	4.607
Reference : Age (31-36)					
Hostel inside campus	1.203	0.574	0.448	0.745	1.944
Hostel outside campus	1.443	1.055	0.304	0.716	2.910
Reference : Accommodation Home					
Intermediate	2.163	4.818	**0.028**	1.086	4.310
Undergraduate	1.886	4.225	**0.039**	1.029	3.456
Reference: Education (Postgraduate)					
Lower class	1.762	0.434	0.509	0.326	9.506
Lower middle class	1.240	0.444	0.505	0.658	2.334
Upper class	1.167	0.039	0.842	0.251	5.424
Upper middle class	0.843	0.496	0.481	0.526	1.353
Reference: Socioeconomic Status (Middle class)					
Not sure	0.859	0.164	0.684	0.413	1.785
Partially	0.868	0.292	0.588	0.521	1.447
Yes	1.360	1.359	0.243	0.810	2.284

Reference: Education as Financial burden (No)					
Married	1.633	0.910	0.339	0.596	4.476
Other	0.557	0.352	0.552	0.081	3.827
Reference: Marital Status (Single)					
A little bit supportive	5.576	16.640	**<0.001**	2.441	12.733
Extremely supportive	1.234	0.619	0.431	0.730	2.088
Not at all supportive	8.282	3.863	**0.049**	1.006	68.178
Somewhat supportive	1.832	6.754	**0.009**	1.160	2.892
Reference: Social Circle Support (Very supportive)					
Obese	0.510	0.746	0.387	0.111	2.345
Overweight	1.079	0.092	0.761	0.658	1.770
Underweight	1.139	0.214	0.643	0.656	1.979
Reference: Body Mass Index (Normal)					
Islamabad Capital Territory	0.735	0.531	0.466	0.321	1.681
Punjab	0.729	0.996	0.318	0.393	1.354
Sindh	0.514	2.547	0.110	0.227	1.163
Other	0.562	1.193	0.274	0.200	1.578
Reference: Province (Khyber Pakhtunkhwa)					

The results from these analyses underscore the importance of gender, perceived financial burden of education, and social support as determinants of mental health issues among students, with social support emerging as a consistent predictor across all three conditions. It is noteworthy that while certain predictors such as living arrangements and socioeconomic status did not always show a significant direct effect, their interaction with other variables like social support may still contribute to the overall risk profile for mental health issues. These findings can inform the development of targeted interventions aimed at mitigating these risks among the student population.

4.4 Machine Learning Approach for Reduction in DASS-21 items

First, through correlation analysis we found the 12 items that had most correlation with scores of mental health issues (depression, anxiety, and stress). Figure 4.1 shows the values of correlation of each item with mental health issues and average correlation. This was followed by feature importance for each item in DASS-21. Figure 4.2 shows the results feature importance section. Table 4.6 shows the combination of feature importance and average correlation to identify top 12 items.

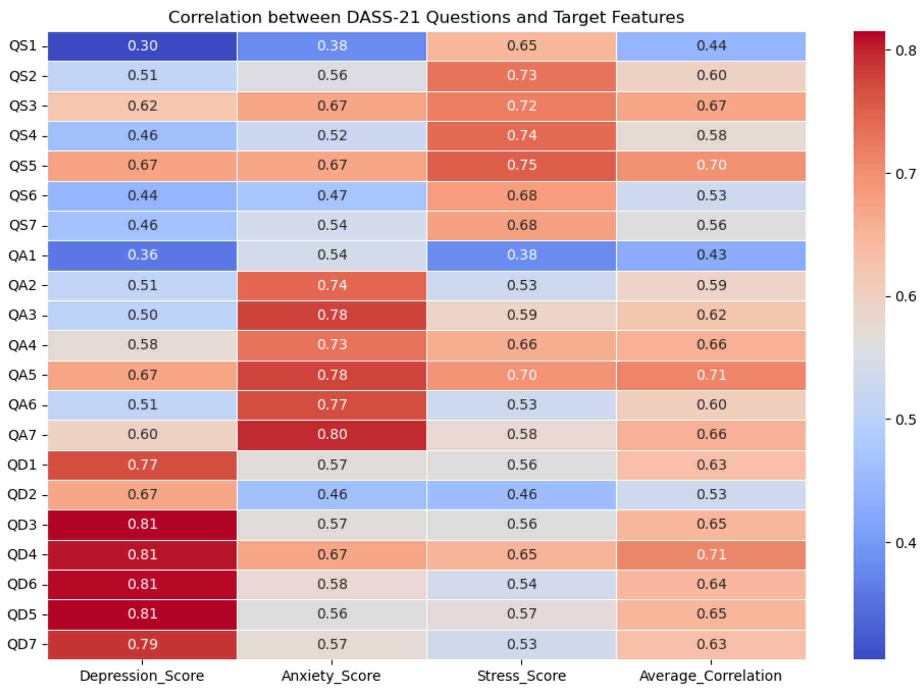

Figure 4.1: Correlation between DASS-21 items and DAS scores.

After that average of both techniques was used to create average importance for each item in DASS-21. This is represented by table below. Where QA, QD, and QS represent Question related to Anxiety, Depression, and Stress respectively. Top 12 questions were selected to train machine learning model. Models were evaluated using metric Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R2). Results for model evaluation before and after hyperparameter tunning are presented in table 4.7.

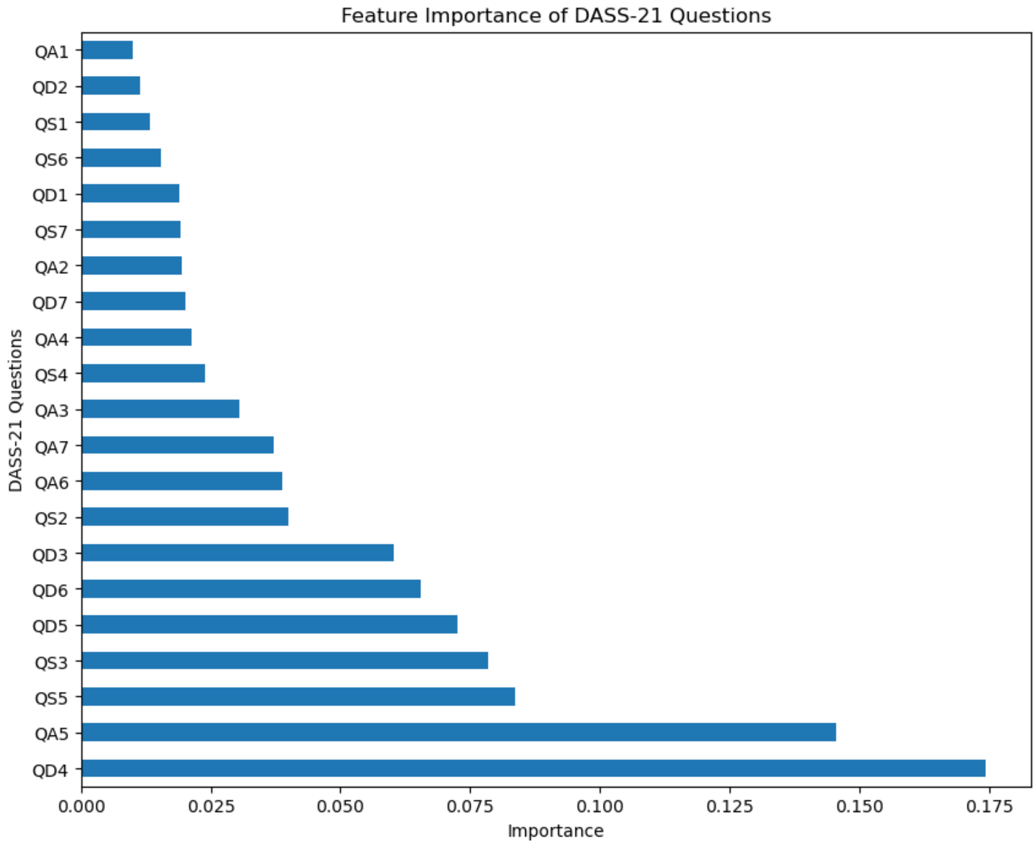

Figure 4.2: Feature importance of DASS-21 items to predict DAS scores.

Table 4.6: Combination of feature importance and correlation.

	Average Correlation	Feature Importance	Average Importance
QD4	0.709626	0.174346	0.441986
QA5	0.713903	0.145599	0.429751
QS5	0.698307	0.083771	0.391039
QS3	0.670119	0.078404	0.374262
QD5	0.648949	0.072582	0.360766
QD6	0.642540	0.065487	0.354013
QD3	0.646835	0.060389	0.353612
QA7	0.656754	0.037203	0.346979
QA4	0.656608	0.021207	0.338908
QA3	0.623210	0.030508	0.326859
QD7	0.631637	0.020186	0.325911
QD1	0.631893	0.018887	0.325390

Table 4.7: Model Evaluation before Hyperparameter Tunning

	MAE	MSE	RMSE	R2	MAE	MSE	RMSE	R2
	Before Hyperparameter tuning				After Hyperparameter tuning			
Linear Regression	2.51	11.57	3.12	0.88	2.51	11.57	3.12	0.88
Decision Tree	4.69	38.53	6.17	0.65	4.48	32.38	5.66	0.71
Random Forest	3.14	16.58	3.94	0.84	3.15	16.46	3.93	0.84
Gradient Boosting	2.72	13.30	3.43	0.87	2.74	13.32	3.43	0.87
Support Vector Regression	3.06	15.27	3.76	0.85	2.49	11.54	3.11	0.88

4.5 Dashboard Interpretation

In order to effectively communicate the findings of our study on mental health prevalence among NUST students, a comprehensive dashboard was developed. The dashboard serves as a dynamic tool for stakeholders to visualize and understand the mental health data in a user-friendly interface.

Figure 4.3 presents a screenshot of the University Students Survey Dashboard. This visualization includes pie charts depicting the distribution of depression, stress, and anxiety scores among the surveyed participants. Each chart categorizes the severity of the mental health condition DASS-21subclasses (normal, mild, moderate, severe, and extremely severe). For instance, the Depression Score Distribution pie chart illustrates a substantial proportion of respondents with moderate to severe symptoms, indicating a pressing need for mental health interventions.

The interactive nature of the dashboard allows for a detailed breakdown by demographic factors, such as age, support system, academic institution, and BMI, to pinpoint specific areas requiring attention. Sample counts are dynamically updated to reflect the filtering criteria applied, ensuring that stakeholders can access tailored insights into the student population's mental health status.

The data represented in the dashboard underscores the nuanced nature of mental health challenges faced by the students. The dashboard not only enhances the stakeholders' understanding but also guides the strategic allocation of resources and the development of targeted support mechanisms.

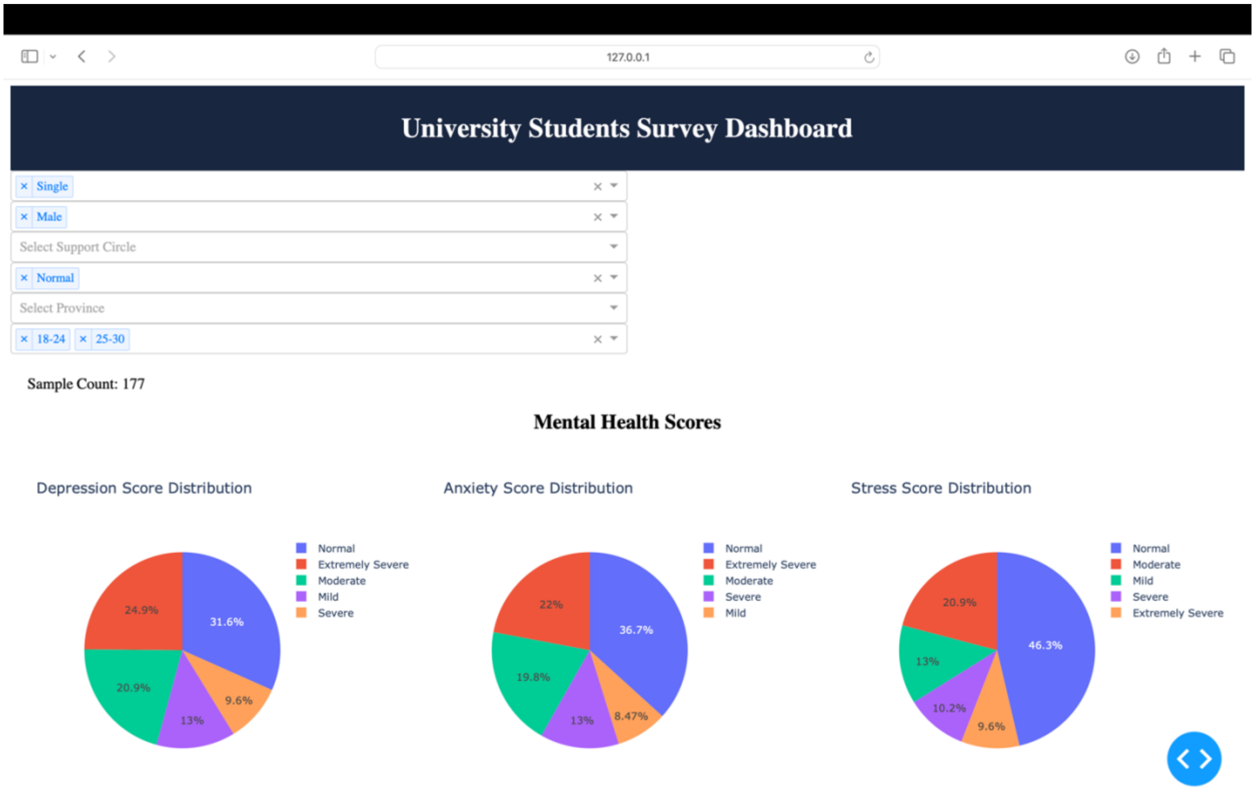

Figure 4.3 Overview of the Dashboard deployed on a local system.

CHAPTER 5: DISCUSSION, FUTURE RECOMMENDATIONS AND CONCLUSION

5.1 Discussion

The findings of our study at the NUST reveal a significant prevalence of depression, anxiety, and stress among students, aligning with the broader trends observed in university settings worldwide. High rates for Extreme severe levels of depression (27.54%), anxiety (31.69%) among university students is alarming but this prevalence echoes the concerns raised by previous studies [4]

[13], who reported a similar trend in university environments. Whereas contradicting literature also exists where researchers did not observe high rates of extreme severe depression or anxiety [44], [53]. This contradiction necessitates the need for further longitudinal and long-term studies.

A notable aspect of findings is the higher odds of female students observing depression, anxiety, and stress, which resonates with the research titled "Brave men and timid women?"[53], [54], who found female university students to be more susceptible to these conditions. This gender disparity in mental health vulnerability necessitates a gender-sensitive approach in developing mental health interventions and support systems.

According to table 3A students with younger age (18-24) have higher odds of depression as compared to students of older age (31-36) which could be a factor of maturity level and being new to university life, this is in agreement with previous studies [20]. Additionally, our findings suggest that students who perceive their education as a financial burden to their families are at a heightened risk for depression compared to those who do not share this concern. This observation is consistent with a scoping review conducted on financial strain and depression, which found that a significant positive association exists between financial strain and depression [55]. Interventions to alleviate such strains included coping mechanisms to improve financial situations, cognitive behaviour modifications, and engaging social support.

Table 3B shows students who are living in hostels outside the university campus (private accommodation) have higher odds of observing anxiety which could be linked to uncertainty of conditions as compared to that of home or hostel inside the campus. This has been discussed in detail in literature [56].

Table 3C shows that the students who have at least completed intermediate, or undergraduate have higher odds of observing stress as compared to those who have completed any form of post graduate studies.

Interestingly, results suggest that stress levels were comparatively lower, with a majority exhibiting normal stress levels. This contrasts with findings in literature that reports high stress levels among college students, often linked to academic pressures [57]. This discrepancy might be attributed to varying cultural or institutional factors and warrants further investigation.

Thesis work also explored the option of item reduction in DASS-21. This has been previously explored but our thesis provides a unique approach as it uses feature engineering technique for item reduction & uses machine learning techniques to evaluate the accuracy of updated questionnaire [17], [38].

Our study also makes a pioneering effort by employing a Dash-based web application for data visualization in mental health assessment. This approach aligns with the technological advancements in mental health monitoring suggested by Torous and Roberts [58], advocating for the integration of digital tools in mental health assessments and interventions.

The implications of our findings extend to various stakeholders, including university authorities, healthcare providers, and policymakers. The need for university authorities to implement comprehensive mental health policies is underscored, echoing Stallman's emphasis on the crucial role of educational institutions in providing a supportive environment for mental health [1]. Additionally, our data offer valuable insights for healthcare providers and policymakers, as literature highlight the need for collaboration between healthcare systems and educational institutions in addressing student mental health concerns [59].

5.2 Future Recommendations

Based on our findings, we recommend the further long-term studies to explore mental health status of university student and development of custom intervention programs that focus on the specific needs of university students. This approach is supported by Conley et al. who evaluated the effectiveness of mental health promotion and prevention programs in higher education [60].

Mental health education should be integrated in the curriculum and the accessibility of mental health resources, including counselling services, safe disclosures, and online support systems, should be made easier and user friendly. Hunt and Eisenberg emphasize the importance of accessibility in mental health interventions, suggesting that improved access can significantly impact student well-being [9].Incorporating mental health education into the university curriculum could contribute to destigmatizing mental health issues and promoting overall well-being of student. The integration of mental health education as a preventative measure in higher education settings has been previously proposed as well [61].

Conducting longitudinal or long-term studies for ongoing assessment of mental health challenges among university students is recommended. This approach will enable us in future to use time series analysis on the data and to help us build better understanding of dynamic nature of the mental health issues. Zivin et al. support this approach, highlighting its importance in understanding the evolving nature of mental health challenges in academic environments [62].

In future, if using artificial intelligence (AI) for mental health monitoring and prediction it would be of essence to use techniques as explainable AI (XAI). XAI focuses on transparency and interpretability, ensuring that AI outputs in mental health applications can be understood by human operators. As for the any health related data, it is of utmost importance to have logical explanation and reasoning for how a conclusion was drawn [63].

Implementation of digital monitoring tools/ solutions, such as the Dash-based system used in study, for continuous monitoring and personalized interventions in mental health is recommended for ease of the stakeholders to understand the data related to mental health status of students. Luxton et al. discuss the potential of mHealth for mental health, emphasizing its role in enhancing behavioural healthcare [64].

5.3 Conclusion:

In conclusion, study conducted at the NUST provides insights into the prevalence and severity of depression, anxiety, and stress among university students. These results should be interpreted with a caution as results represent data in one point of time and may not be represent completely the dynamic nature of university students. The application of the DASS-21 scale and binary logistic regression analysis has enabled a comprehensive understanding of how factors such as gender, age, financial stability, type of accommodation, and social support networks influence students' mental health.

Our findings indicate a concerning level of mental health issues within the student population, with depression and anxiety being particularly prevalent. This emphasizes a need for university authorities and mental health professionals to prioritize and address these challenges. Proactive measures, such as development of custom targeted intervention programs, increased accessibility to mental health resources, use of digital tools to monitor mental health status and incorporating mental health education into the university curriculum, are imperative.

Furthermore, the use of a Dash-based web application for data visualization in our study exemplifies the potential of digital tools in enhancing the effectiveness of mental health assessments and interventions. This approach not only aids in the clear communication of complex data to stakeholders but also opens new avenues for ongoing monitoring and support for students' mental health.

CHAPTER 6: REFERENCE:

[1] H. M. Stallman, ‘Psychological distress in university students: A comparison with general population data’, *Aust Psychol*, vol. 45, no. 4, pp. 249–257, Dec. 2010, doi: 10.1080/00050067.2010.482109.

[2] D. Eisenberg, S. E. Gollust, E. Golberstein, and J. L. Hefner, ‘Prevalence and Correlates of Depression, Anxiety, and Suicidality Among University Students’, *American Journal of Orthopsychiatry*, vol. 77, no. 4, pp. 534–542, Oct. 2007, doi: 10.1037/0002-9432.77.4.534.

[3] M. Prince *et al.*, ‘No health without mental health’, *859 Global Mental Health*, vol. 8, 2007, doi: 10.1016/S0140.

[4] A. K. Ibrahim, S. J. Kelly, C. E. Adams, and C. Glazebrook, ‘A systematic review of studies of depression prevalence in university students’, *Journal of Psychiatric Research*, vol. 47, no. 3. Elsevier Ltd, pp. 391–400, 2013. doi: 10.1016/j.jpsychires.2012.11.015.

[5] ‘Fall 2017 Reference Group Executive Summary’. [Online]. Available: www.acha.org,

[6] ‘DIAGNOSTIC AND STATISTICAL MANUAL OF DSM-5 ™’.

[7] R. C. Kessler, T. C. Wai, O. Demler, and E. E. Walters, ‘Prevalence, severity, and comorbidity of 12-month DSM-IV disorders in the National Comorbidity Survey Replication’, *Archives of General Psychiatry*, vol. 62, no. 6. pp. 617–627, Jun. 2005. doi: 10.1001/archpsyc.62.6.617.

[8] ‘collegestudentsacademicstressanditsrelationtoanxietytimemanagementandleisuresatisfaction’.

[9] J. Hunt and D. Eisenberg, ‘Mental Health Problems and Help-Seeking Behavior Among College Students’, *Journal of Adolescent Health*, vol. 46, no. 1. pp. 3–10, Jan. 2010. doi: 10.1016/j.jadohealth.2009.08.008.

[10] M. M. Hossain, M. A. Alam, and M. H. Masum, ‘Prevalence of anxiety, depression, and stress among students of Jahangirnagar University in Bangladesh’, *Health Sci Rep*, vol. 5, no. 2, Mar. 2022, doi: 10.1002/hsr2.559.

[11] E. R. Weitzman, ‘Poor Mental Health, Depression, and Associations with Alcohol Consumption, Harm, and Abuse in a National Sample of Young Adults in College’, *Journal of Nervous and Mental Disease*, vol. 192, no. 4, pp. 269–277, Apr. 2004, doi: 10.1097/01.nmd.0000120885.17362.94.

[12] H. A. Fillmore, ‘The effect of daily internet usage on a short attention span and academic performance’.

[13] G. X. D. Tan, X. C. Soh, A. Hartanto, A. Y. H. Goh, and N. M. Majeed, ‘Prevalence of anxiety in college and university students: An umbrella review’, *Journal of Affective Disorders Reports*, vol. 14. Elsevier B.V., Dec. 01, 2023. doi: 10.1016/j.jadr.2023.100658.

[14] S. Sultan *et al.*, ‘Prevalence of depression, anxiety, stress and its relationship with knowledge about COVID-19 in medical and laboratory medicine students of Umm-Al-Qura

University: a cross-sectional survey', *Egyptian Journal of Neurology, Psychiatry and Neurosurgery*, vol. 58, no. 1, Dec. 2022, doi: 10.1186/s41983-022-00590-7.

[15] A. Schulze, F. Brand, J. Geppert, and G. F. Böl, 'Digital dashboards visualizing public health data: a systematic review', *Frontiers in Public Health*, vol. 11. Frontiers Media S.A., 2023. doi: 10.3389/fpubh.2023.999958.

[16] I. Arvelo and A. Plantinga, 'U.S. Mental Health Dashboard', *The New England Journal of Statistics in Data Science*, pp. 1–7, Dec. 2023, doi: 10.51387/23-NEJSDS52.

[17] R. P. Monteiro, G. L. de H. Coelho, P. H. P. Hanel, V. V. Gouveia, and R. Vilar, 'The 12-Item Mini-DASS: A Concise and Efficient Measure of Depression, Anxiety, and Stress', *Appl Res Qual Life*, Dec. 2023, doi: 10.1007/s11482-023-10214-8.

[18] A. M. Ali, A. A. Alkhamees, H. Hori, Y. Kim, and H. Kunugi, 'The depression anxiety stress scale 21: Development and validation of the depression anxiety stress scale 8-item in psychiatric patients and the general public for easier mental health measurement in a post COVID-19 world', *Int J Environ Res Public Health*, vol. 18, no. 19, Oct. 2021, doi: 10.3390/ijerph181910142.

[19] R. P. Auerbach *et al.*, 'Mental disorders among college students in the World Health Organization World Mental Health Surveys', *Psychological Medicine*, vol. 46, no. 14. Cambridge University Press, pp. 2955–2970, Oct. 01, 2016. doi: 10.1017/S0033291716001665.

[20] M. N. Khan, P. Akhtar, S. Ijaz, and A. Waqas, 'Prevalence of Depressive Symptoms Among University Students in Pakistan: A Systematic Review and Meta-Analysis', *Frontiers in*

Public Health, vol. 8. Frontiers Media S.A., Jan. 08, 2021. doi: 10.3389/fpubh.2020.603357.

[21] F. Campbell *et al.*, ‘Factors that influence mental health of university and college students in the UK: a systematic review’, *BMC Public Health*, vol. 22, no. 1, Dec. 2022, doi: 10.1186/s12889-022-13943-x.

[22] N. Bayram and N. Bilgel, ‘The prevalence and socio-demographic correlations of depression, anxiety and stress among a group of university students’, *Soc Psychiatry Psychiatr Epidemiol*, vol. 43, no. 8, pp. 667–672, Apr. 2008, doi: 10.1007/s00127-008-0345-x.

[23] D. P. Goldberg *et al.*, ‘The validity of two versions of the GHQ in the WHO study of mental illness in general health care’, *Psychol Med*, vol. 27, no. 1, pp. 191–197, Jan. 1997, doi: 10.1017/S0033291796004242.

[24] R. C. Kessler *et al.*, ‘Short screening scales to monitor population prevalences and trends in non-specific psychological distress’, *Psychol Med*, vol. 32, no. 6, pp. 959–976, Aug. 2002, doi: 10.1017/S0033291702006074.

[25] R. C. Kessler *et al.*, ‘Screening for Serious Mental Illness in the General Population’.

[26] R. L. Spitzer, K. Kroenke, J. B. W. Williams, and B. Löwe, ‘A Brief Measure for Assessing Generalized Anxiety Disorder The GAD-7’.

[27] C. W. Topp, S. D. Østergaard, S. Søndergaard, and P. Bech, 'The WHO-5 well-being index: A systematic review of the literature', *Psychother Psychosom*, vol. 84, no. 3, pp. 167–176, Apr. 2015, doi: 10.1159/000376585.

[28] P. F. Lovibond and S. H. Lovibond, 'THE STRUCTURE OF NEGATIVE EMOTIONAL STATES: COMPARISON OF THE DEPRESSION ANXIETY STRESS SCALES (DASS) WITH THE BECK DEPRESSION AND ANXIETY INVENTORIES', 1995.

[29] J. D. Henry and J. R. Crawford, 'The short-form version of the Depression anxiety stress scales (DASS-21): Construct validity and normative data in a large non-clinical sample', *British Journal of Clinical Psychology*, vol. 44, no. 2, pp. 227–239, Jun. 2005, doi: 10.1348/014466505X29657.

[30] T. Kock Wah, K. Abd Ghani, and N. Fatihah Mat Yusoff, 'THE GOODNESS-OF-FIT OF DASS-21MODELS AMONG UNIVERSITY STUDENTS', 2016.

[31] S. Shelly *et al.*, 'Mental health services data dashboards for reporting to Australian governments during COVID-19', *Int J Environ Res Public Health*, vol. 18, no. 19, Oct. 2021, doi: 10.3390/ijerph181910514.

[32] M. Ghazisaeidi, R. Safdari, M. Torabi, M. Mirzaee, J. Farzi, and A. Goodini, 'Development of performance dashboards in healthcare sector: Key practical issues', *Acta Informatica Medica*, vol. 23, no. 5, pp. 317–321, 2015, doi: 10.5455/aim.2015.23.317-321.

[33] O. M. Yigitbasioglu and O. Velcu, 'A review of dashboards in performance management: Implications for design and research', *International Journal of Accounting Information Systems*, vol. 13, no. 1, pp. 41–59, Mar. 2012, doi: 10.1016/j.accinf.2011.08.002.

[34] S. Housbane, A. Khoubila, K. Ajbal, M. Agoub, O. Battas, and M. B. Othmani, ‘Real-time monitoring system to manage mental healthcare emergency unit’, *Healthc Inform Res*, vol. 26, no. 4, pp. 344–350, 2020, doi: 10.4258/hir.2020.26.4.344.

[35] S. H. Scholle and A. D. Naik, ‘A Person-Centered Care Dashboard for Individuals with Complex Health Care Needs - Charting a Course for the Future’, *JAMA Network Open*. American Medical Association, p. E2224945, 2022. doi: 10.1001/jamanetworkopen.2022.24945.

[36] S. Shelly *et al.*, ‘Mental health services data dashboards for reporting to Australian governments during COVID-19’, *Int J Environ Res Public Health*, vol. 18, no. 19, Oct. 2021, doi: 10.3390/ijerph181910514.

[37] Y. Wang and N. Hajli, ‘Exploring the path to big data analytics success in healthcare’, *J Bus Res*, vol. 70, pp. 287–299, Jan. 2017, doi: 10.1016/j.jbusres.2016.08.002.

[38] R. P. Monteiro, G. L. de H. Coelho, P. H. P. Hanel, V. V. Gouveia, and R. Vilar, ‘The 12-Item Mini-DASS: A Concise and Efficient Measure of Depression, Anxiety, and Stress’, *Appl Res Qual Life*, Dec. 2023, doi: 10.1007/s11482-023-10214-8.

[39] A. M. Ali, A. A. Alkhamees, H. Hori, Y. Kim, and H. Kunugi, ‘The depression anxiety stress scale 21: Development and validation of the depression anxiety stress scale 8-item in psychiatric patients and the general public for easier mental health measurement in a post COVID-19 world’, *Int J Environ Res Public Health*, vol. 18, no. 19, Oct. 2021, doi: 10.3390/ijerph181910142.

[40] E. H. Lee *et al.*, ‘The 21-Item and 12-Item Versions of the Depression Anxiety Stress Scales: Psychometric Evaluation in a Korean Population’, *Asian Nurs Res (Korean Soc Nurs Sci)*, vol. 13, no. 1, pp. 30–37, Feb. 2019, doi: 10.1016/j.anr.2018.11.006.

[41] J. E. Bartlett, J. W. Kotrlik, and C. C. Higgins, ‘Organizational Research: Determining Organizational Research: Determining Appropriate Sample Size in Survey Research Appropriate Sample Size in Survey Research’, 2001.

[42] P. F. Lovibond and S. H. Lovibond, ‘THE STRUCTURE OF NEGATIVE EMOTIONAL STATES: COMPARISON OF THE DEPRESSION ANXIETY STRESS SCALES (DASS) WITH THE BECK DEPRESSION AND ANXIETY INVENTORIES’, 1995.

[43] H. Waqar and G. Amir, ‘Translation, adaptation and validation of Depression, Anxiety and Stress Scale in Urdu’, *Insights on the Depression and Anxiety*, vol. 4, no. 1, pp. 001–004, Feb. 2020, doi: 10.29328/journal.ida.1001011.

[44] F. Rizvi, A. Qureshi, A. Rajput, and M. Afzal, ‘Prevalence of Depression, Anxiety and Stress (by DASS Scoring System) among Medical Students in Islamabad, Pakistan’, *Br J Med Med Res*, vol. 8, no. 1, pp. 69–75, Jan. 2015, doi: 10.9734/bjmmr/2015/17193.

[45] E. Chung, G. Subramaniam, and L. C. Dass, ‘Online learning readiness among university students in Malaysia amidst Covid-19’, *Asian Journal of University Education*, vol. 16, no. 2, pp. 45–58, Jul. 2020, doi: 10.24191/AJUE.V16I2.10294.

[46] H. Shahid *et al.*, ‘The Severity of Depression, Anxiety, and Stress: Recommendations From Joint Work of Research Center and Psychology Clinics in COVID-19 Pandemic’, *Front Psychiatry*, vol. 13, Jun. 2022, doi: 10.3389/fpsyt.2022.839542.

[47] P. D. Bengwasan, A. B. I. Bernardo, and S. I. Maximo, 'Translation and Initial Validation of the Depression Anxiety and Stress Scale (DASS-21) in Ilokano', *Psychol Stud (Mysore)*, vol. 67, no. 4, pp. 594–604, Dec. 2022, doi: 10.1007/s12646-022-00696-1.

[48] I. N. Beaufort, G. H. De Weert-Van Oene, V. A. J. Buwalda, J. Rob, J. De Leeuw, and A. E. Goudriaan, 'The Depression, Anxiety and Stress Scale (DASS-21) as a Screener for Depression in Substance Use Disorder Inpatients', *Addiction Research*, vol. 23, no. 5, pp. 260–268, 2017, doi: 10.2307/26792397.

[49] A. Rybak, 'Survey mode and nonresponse bias: A meta-Analysis based on the data from the international social survey programme waves 1996 2018 and the European social survey rounds 1 to 9', *PLoS One*, vol. 18, no. 3 March, Mar. 2023, doi: 10.1371/journal.pone.0283092.

[50] M. Kuznetsova *et al.*, 'An analysis of the structure and content of dashboards used to monitor patient safety in the inpatient setting', *JAMIA Open*, vol. 4, no. 4, Oct. 2021, doi: 10.1093/jamiaopen/ooab096.

[51] M. Karami, M. Langarizadeh, and M. Fatehi, 'Evaluation of Effective Dashboards: Key Concepts and Criteria', *Open Med Inform J*, vol. 11, no. 1, pp. 52–57, Oct. 2017, doi: 10.2174/1874431101711010052.

[52] S. Almasi, K. Bahaadinbeigy, H. Ahmadi, S. Sohrabei, and R. Rabiei, 'Usability Evaluation of Dashboards: A Systematic Literature Review of Tools', *BioMed Research International*, vol. 2023. Hindawi Limited, 2023. doi: 10.1155/2023/9990933.

[53] M. N. Gitay *et al.*, ‘Gender Differences and Prevalence of Mental Health Problems in Students of Healthcare Units’, *Community Ment Health J*, vol. 55, no. 5, pp. 849–853, Jul. 2019, doi: 10.1007/s10597-018-0304-2.

[54] C. P. McLean and E. R. Anderson, ‘Brave men and timid women? A review of the gender differences in fear and anxiety’, *Clinical Psychology Review*, vol. 29, no. 6. pp. 496–505, Aug. 2009. doi: 10.1016/j.cpr.2009.05.003.

[55] C. K. Ettman *et al.*, ‘Financial strain and depression in the U.S.: a scoping review’, *Translational Psychiatry*, vol. 13, no. 1. Springer Nature, Dec. 01, 2023. doi: 10.1038/s41398-023-02460-z.

[56] J. D. Worsley, P. Harrison, and R. Corcoran, ‘The role of accommodation environments in student mental health and wellbeing’, *BMC Public Health*, vol. 21, no. 1, Dec. 2021, doi: 10.1186/s12889-021-10602-5.

[57] R. Beiter *et al.*, ‘The prevalence and correlates of depression, anxiety, and stress in a sample of college students’, *J Affect Disord*, vol. 173, pp. 90–96, Mar. 2015, doi: 10.1016/j.jad.2014.10.054.

[58] J. Torous and L. W. Roberts, ‘Needed innovation in digital health and smartphone applications for mental health transparency and trust’, *JAMA Psychiatry*, vol. 74, no. 5. American Medical Association, pp. 437–438, May 01, 2017. doi: 10.1001/jamapsychiatry.2017.0262.

[59] ‘Eisenberg, Golberstein, & Hunt -- May 2 2009’.

[60] C. S. Conley, J. A. Durlak, and D. A. Dickson, 'An evaluative review of outcome research on universal mental health promotion and prevention programs for higher education students', *Journal of American College Health*, vol. 61, no. 5. pp. 286–301, Jul. 01, 2013. doi: 10.1080/07448481.2013.802237.

[61] N. Reavley and A. F. Jorm, 'Prevention and early intervention to improve mental health in higher education students: A review', *Early Intervention in Psychiatry*, vol. 4, no. 2. pp. 132–142, May 2010. doi: 10.1111/j.1751-7893.2010.00167.x.

[62] K. Zivin, D. Eisenberg, S. E. Gollust, and E. Golberstein, 'Persistence of mental health problems and needs in a college student population', *J Affect Disord*, vol. 117, no. 3, pp. 180–185, Oct. 2009, doi: 10.1016/j.jad.2009.01.001.

[63] D. W. Joyce, A. Kormilitzin, K. A. Smith, and A. Cipriani, 'Explainable artificial intelligence for mental health through transparency and interpretability for understandability', *npj Digital Medicine*, vol. 6, no. 1. Nature Research, Dec. 01, 2023. doi: 10.1038/s41746-023-00751-9.

[64] D. D. Luxton, R. A. McCann, N. E. Bush, M. C. Mishkind, and G. M. Reger, 'MHealth for mental health: Integrating smartphone technology in behavioral healthcare', *Prof Psychol Res Pr*, vol. 42, no. 6, pp. 505–512, Dec. 2011, doi: 10.1037/a0024485.

APPENDIX

1. DASS-21 Questionnaire

The rating scale is as follows
0 Did not apply to me at all 1 Applied to me to some degree or some of the time 2 Applied to me to a considerable degree or a good part of the time 3 Applied to me very much or most of the time

1 (s)	I found it hard to wind down	0	1	2	3
2 (a)	I was aware of dryness of my mouth	0	1	2	3
3 (d)	I couldn't seem to experience any positive feeling at all	0	1	2	3
4 (a)	I experienced breathing difficulty (e.g. excessively rapid breathing, breathlessness in the absence of physical exertion)	0	1	2	3
5 (d)	I found it difficult to work up the initiative to do things	0	1	2	3

6 (s)	I tended to over-react to situations	0	1	2	3
7 (a)	I experienced trembling (e.g. in the hands)	0	1	2	3
8 (s)	I felt that I was using a lot of nervous energy	0	1	2	3
9 (a)	I was worried about situations in which I might panic and make a fool of myself	0	1	2	3
10 (d)	I felt that I had nothing to look forward to	0	1	2	3
11 (s)	I found myself getting agitated	0	1	2	3
12 (s)	I found it difficult to relax	0	1	2	3
13 (d)	I felt downhearted and blue	0	1	2	3
14 (s)	I was intolerant of anything that kept me from getting on with what I was doing	0	1	2	3
15 (a)	I felt I was close to panic	0	1	2	3

16 (d)	I was unable to become enthusiastic about anything	0	1	2	3
17 (d)	I felt I wasn’t worth much as a person	0	1	2	3
18 (s)	I felt that I was rather touchy	0	1	2	3
19 (a)	I was aware of the action of my heart in the absence of physical exertion (e.g. sense of heart rate increase, heart missing a beat)	0	1	2	3
20 (a)	I felt scared without any good reason	0	1	2	3
21 (d)	I felt that life was meaningless	0	1	2	3