Pre-thesis -II Report

Enhancing Stress Management and Mental Wellness in Bangladesh for Undergraduate Students Through NLP and HCI

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Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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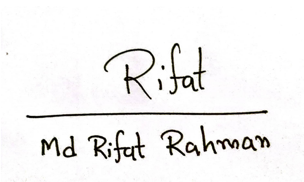

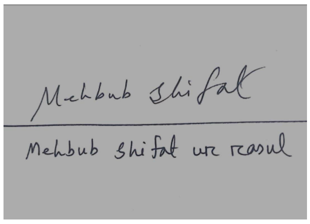

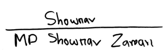

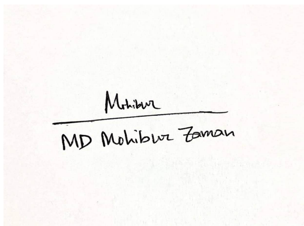

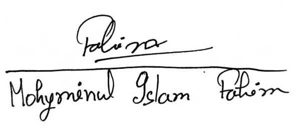

Approval

The thesis/project titled “Enhancing Stress Management and Mental Wellness in Bangladesh for Undergraduate Students through NLP and HCI” submitted by

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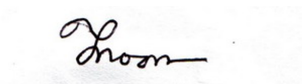

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Chapter 1

Abstract

To address the mental well-being and stress management of undergraduates within the contemporary digital education landscape, characterized by increasingly significant challenges, this study seeks to establish a comprehensive system. This system will harmonize natural language processing (NLP) techniques for understanding emotions and language with human-computer interaction (HCI) principles for designing user-friendly interfaces. Furthermore, the study will employ both qualitative and quantitative research techniques, including qualitative interviews and quantitative surveys, to gain a holistic understanding of undergraduates' mental health needs. In addition, snowball sampling will be employed to identify potential participants for the qualitative interviews, ensuring a diverse and representative sample. The integration of these research methodologies, along with the utilization of NLP models such as BERT, RoBERTa, and DistilBERT, aims to equip undergraduates with valuable tools for self-reflection, emotional support, and effective stress management during their academic journey. This multifaceted approach will ultimately contribute to promoting a healthier and more productive undergraduate experience, accentuating the significance of user-centric HCI in addressing the well-being of students.

Keywords: HCI, dataset, mental health, model, diagnosis

Chapter 2

Introduction

In modern society, characterized by the continuous speed of daily existence, the imperative for proficient stress management and the advancement of mental well-being has been increasingly apparent. As we commence an investigation into the convergence of technology, culture, and the welfare of undergraduate students in Bangladesh, we are confronted with a compelling imperative to tackle the immediate obstacles encountered by this particular population. The field of mental health on a global scale is currently experiencing a significant shift, characterized by exceptional difficulties and improvements in technology. Bangladesh is positioned as a leading participant in this revolutionary movement. The significance of stress management and mental well-being extends beyond national boundaries, as demonstrated by extensive global research. Following the onset of the COVID-19 epidemic, an investigation carried out in the United States [28] extensively examined the repercussions of this worldwide disaster on the psychological well-being of university students. The results revealed a striking truth - a significant increase in the prevalence of severe depression, anxiety, and heightened stress levels among students. This insight serves as a reminder of the urgent requirement for creative solutions aimed at addressing mental health difficulties since they have significant repercussions for both individuals and society at large. Concurrently, the amalgamation of machine learning and mental health care [27] portrays a scenario wherein technology assumes a crucial function in the identification, assessment, and intervention of mental health disorders. The investigation into the utilization of social media data and machine learning techniques for the purpose of forecasting mental health conditions [14] presents a promising avenue for the early identification and intervention of such conditions. However, this field has ethical quandaries, necessitating cautious consideration and decision-making. In addition, there is research that explores the subtle complexity of human behavior and communication, utilizing signal processing and machine learning techniques [11] in order to deduce mental states. The researchers explore the impact of mental health support system design on individuals' paths to well-being [30]. They also conduct experiments including innovative interventions, such as the utilization of blue light for stress relief [23]. These investigations shed light on the various complex ways in which technology can influence mental well-being. As our attention shifts towards Bangladesh, a country characterized by its peculiar socio-cultural composition and the specific obstacles encountered by its undergraduate students, we find ourselves at a pivotal juncture. The internet has been recognized as a potent tool, as seen by a study carried out in Australia [6], which highlights the significant impact of online services, such as mental health helplines, in effectively addressing those experiencing distress. The ongoing development of technology-based mental health support systems persists, exemplified by the emergence of programs such as Flip*Doubt [31], which are specifically designed to assist users in effectively controlling negative thoughts. These applications offer a look into the potential of incorporating artificial intelligence and machine learning into cognitive reappraisal interventions, hence enhancing the accessibility of stress management and mental wellness services for individuals requiring assistance. In order to provide direction for our endeavors in Bangladesh, a comprehensive set of design principles for technology-based interventions in the field of mental health therapy [7] is established. These guidelines underscore the importance of collaboration, therapeutic frameworks, individualized client considerations, and privacy. The valuable understanding of young adults' inclination towards internet resources and self-screeners, particularly those who are hesitant to seek conventional treatment, is derived from the insights obtained through focus groups [35]. Novel technologies, like mental health chatbots [37], virtual reality, and serious games [38], present a departure from conventional limits in the domain of mental health care. These advancements prompt us to venture into uncharted territories within Human-Computer Interaction (HCI). Integrating HCI concepts with electronic mental health interventions underscores the importance of interdisciplinary cooperation in developing solutions that prioritize users' needs while ensuring their safety and effectiveness [21]. The attention of researchers is drawn to the convergence of HCI4D (Human-Computer Interaction for Development) and mental health research in Bangladesh, where the influence of cultural nuances and socio-economic determinants on mental health is significant [18]. Upon entering this domain, it becomes evident that there is a requirement for research studies that adhere to ethical principles, demonstrate cultural sensitivity, and prioritize the well-being and involvement of participants. The utilization of technology-based data derived from activity trackers, such as Fitbit [17], offers a promising avenue for providing assistance to persons grappling with mental health challenges. Nonetheless, undertaking this endeavor necessitates meticulous deliberation, substantiation, and a concerted endeavor to address ethical considerations. Human-Computer Interaction (HCI) has been identified as a crucial element in addressing the digital divide in mental health treatment, fostering interdisciplinary cooperation, and developing AI-driven solutions that are user-friendly, ethical, and efficient [33]. It prompts us to investigate innovative methodologies, such as virtual reality and immersive video games, in order to augment therapeutic results. In the context of Bangladesh, where there is a convergence of intricate health requirements and mental health difficulties [19], technology is a crucial means of support. The integration of a social model framework with contemporary medical interventions holds the potential to enhance personal agency, prioritizing their requirements and lived encounters within the realm of technical advancements. In this regard, as we commence our endeavor to improve mental health care in Bangladesh, we acknowledge the imperative nature [4]of providing easily accessible, captivating, and cost-effective mental health therapies. The advent of technology presents itself as a potentially viable solution, albeit not without its inherent difficulties. The key to a more promising future lies in the collaboration of specialists in Human-Computer Interaction (HCI) and professionals in the field of mental health. This research work aims to utilize the capabilities of Natural Language Processing (NLP), Human-Computer Interaction (HCI), and advanced technology to improve stress management and mental well-being among undergraduate students in Bangladesh. By synthesizing findings from a wide range of international scholarly investigations, our objective is to navigate the intricate interplay between culture, technology, and human experiences, while maintaining a resolute dedication to cultivating a society that is more inclusive and supportive. As we further investigate this subject matter, we find ourselves at the forefront of a transformative period, when the intersection of technology and empathy holds the potential to redefine the trajectory of mental healthcare. In this undertaking, it is acknowledged that the endeavor to address stress management and promote mental well-being is not solely a matter of personal preference, but rather a need, as it profoundly influences the well-being and aspirations of numerous individuals, hence influencing the trajectory of a society.

Chapter 3

Problem Statement

The research mentioned in [28] offers a compelling depiction of the considerable scale of mental health challenges encountered by university students, although within a Western framework. The results of this study emphasize the pressing necessity for further research and interventions aimed at addressing mental health issues among college students, particularly in light of the COVID-19 pandemic. The findings of the study indicate that a significant proportion of the participants reported experiencing severe symptoms of sadness, anxiety, and even thoughts of suicide. The majority of the kids in question also indicated a heightened level of stress and a deficiency in effective coping strategies. While this study focuses on American college students, its findings resonate with the broader global trend of deteriorating mental health among young adults. The aforementioned pattern calls for a comprehensive comprehension of the elements that contribute to mental health problems and inventive interventions that are customized to certain cultural and educational settings.
In recent times, the utilization of technology has witnessed a growing prominence in its contribution towards addressing mental health concerns. The integration of disciplines such as machine learning, analysis of social media data, and Human-Computer Interaction (HCI) has created novel opportunities for the advancement of digital interventions. The study conducted by [27] investigates the potential applications of machine learning (ML) in the identification, diagnosis, and treatment of mental health disorders. This manuscript critically examines a significant corpus of research from the fields of computers and human-computer interaction (HCI), with the aim of discovering recurring patterns, areas of research that have not been adequately explored, and obstacles that need to be addressed. This statement underscores the necessity of employing interdisciplinary methodologies and conducting thorough evaluations of the individual, societal, and ethical ramifications of machine learning in practical mental health settings.

In addition, the application of machine learning and social media data for forecasting mental health states is examined in [14]. While this phenomenon emphasizes the possibility of identifying and addressing mental problems at an early stage, it also brings attention to issues such as unreliable prognostications, lack of accountability among involved parties, and the presence of biases. This report classifies these challenges into various domains, including ethics committees in social media research, data veracity, and ramifications for stakeholders, underscoring the imperative for responsible and ethical advancement in the discipline.

The field of human-computer interaction (HCI) has emerged as a significant area of study in the context of mental health. The significance of Human-Computer Interaction (HCI) in augmenting mental health support systems is of utmost importance. The study conducted by [30] focuses on the design of a mental health helpline system in India. It highlights the significance of taking into account socio-cultural variables and the specific requirements of marginalized individuals who seek assistance through the helpline. The paper finishes by providing suggestions for the design of technology-mediated systems aimed at providing mental health support. The set of design standards for technology-driven solutions in mental health treatment is introduced in [7]. These standards contain a range of issues, encompassing the design process, considerations, and evaluation procedure. The objective of these principles is to improve the accessibility, engagement, effectiveness, and affordability of mental health support using technology, as demonstrated by real-world projects. The existing body of literature offers useful insights into mental health difficulties and prospective technological interventions. However, it is evident that there is a study shortage specific to the setting of Bangladesh. Localized treatments are necessary in Bangladesh due to the various socio-cultural elements, educational system, and prevailing stresses present in the country.

Furthermore, the extent to which Natural Language Processing (NLP) approaches have been thoroughly investigated in the context of Bangladesh remains insufficient. The emergence of focused digital interventions in mental health services, specifically through the utilization of natural language processing (NLP)–based chatbots, is emphasized in the study cited as [37]. These chatbots utilize natural language processing (NLP) to provide therapeutic support by understanding and interpreting human language. Nevertheless, the extent to which these technologies can be applied in Bangladesh has not been thoroughly investigated. Hence, the primary objective of this study is to address this disparity by examining the potential of integrating Natural Language Processing (NLP) and Human-Computer Interaction (HCI) to create culturally relevant and efficacious interventions targeting stress management and mental well-being among undergraduate students in Bangladesh.

Chapter 4

Research Objective

The main motivation of our research is to provide solutions to different mental illnesses. For this, we need to classify stress depression, and different mental disorders. Considering all of this the objective of our research will be:

- Classifying Mental disorders
- Based on the prediction provide a stress management solution
- Provide a suggestion based on the user scenario

Chapter 5

Literature Review

Author Hegde S. [28] investigates the impact of COVID-19 on the mental health of US college students in a large university system. The study used an online survey, including depression and anxiety scales, along with questions on COVID-19 stressors and coping. The findings show many of the 2031 participants had severe depression, anxiety, and suicidal thoughts. Most reported increased stress and inadequate coping abilities. This study underscores the urgent need for research and interventions to address mental health challenges among college students during the pandemic.
In their article [27], the authors explore the intersection of machine learning (ML) and mental health care. They highlight ML's potential in detecting, diagnosing, and treating mental health issues. The paper reviews 54 works from computing and human-computer interaction (HCI) literature, identifying common themes, gaps, and challenges. This research aims to guide future efforts and promote ML applications in mental health. Key findings emphasize the need for human-centered and interdisciplinary approaches and a comprehensive assessment of the personal, social, and ethical implications of ML in real-world mental health contexts. This article is a foundational resource for advancing ML and mental health research.
Here Chancellor S. [14] explores machine learning and social media data for predicting mental health states. It highlights their potential for early detection and treatment of mental disorders, while also noting associated risks such as inaccurate predictions, unaccountable actors, and biases. The paper categorizes concerns into three areas: ethics committees in social media research, validity, data, and machine learning questions, and implications for stakeholders. It concludes by urging action to address these interdisciplinary dilemmas and ensure responsible and ethical progress in the field.
Author Bone D. [11] tackles the problem of identifying hidden attributes in a system modulating body signals. It uses signal processing and machine learning on diverse sensor data. The process involves refining, localizing, and demonizing signals like speech patterns from visual, auditory, and physiological sources. It also considers the impact of external factors and communicative partners on behavior through time-series modeling. Machine learning is then used to infer mental states, aiding decision-making for humans and autonomous systems.
In paper [30] the Author examines how the design of the Indian mental health helpline system affects individuals seeking care for distress. It acknowledges that individuals in distress often take unique paths to find care, and the initial resource

they access can influence their recovery. The research involves interviews with 18 stakeholders, including past helpline users, to uncover how they navigate barriers when seeking help. Using a design justice framework rooted in Amartya Sen's realization-focused justice, it discusses the implications of these findings. The study concludes with recommendations for designing technology-mediated mental health support systems, emphasizing the importance of considering sociocultural factors and marginalized caller needs.

The study of Daher K. [23] explores machines demonstrating empathy to alleviate distress, a contributor to health issues. It focuses on using blue light to reduce stress. In an experiment with 17 participants, a stress-inducing test was conducted while monitoring physiological signals with an Empatica E4 device. The results show that blue light reduced stress, maintaining lower stress levels compared to the normal state. This study suggests the potential of simple interventions, like blue light, to mitigate mental stress in individuals.

The study [6], which was done in Australia in 2008, sought to examine the internet usage patterns of individuals aged 12–25 and evaluate the efficacy of online resources in addressing mental health concerns. The investigators carried out a cross-sectional survey utilizing telephone interviews to collect data from a sample of 2000 participants picked at random. The study revealed that a considerable proportion of adolescents utilized the internet for the purpose of engaging in social networking activities and seeking information pertaining to mental health concerns, irrespective of their own personal experiences with such issues. Approximately 20% of the study participants had reported a history of mental health disorders within the preceding five-year period. Notably, a significant proportion of these individuals had utilized online resources to seek information pertaining to their respective conditions. The research elucidated variations in internet utilization patterns and resource preferences contingent upon age and gender. The researchers have reached the conclusion that technology, specifically the internet, plays a crucial role in the lives of young individuals. Consequently, online mental health services should provide a diverse range of resources that cater to various age groups and both genders. These resources should include features such as question-and-answer forums and email support in order to effectively meet the needs of the target audience.

The paper of author Svetlana Yarosh[31] demonstrated Flip*Doubt which is a web application designed to aid users in managing negative thoughts associated with mental health issues, particularly targeting cognitive reappraisal. Through a one-month field deployment involving 13 graduate students, it collects a dataset of negative thoughts paired with positive reframes and provides insights into how individuals utilize this crowd-powered system in real-life situations. The research yields a qualitative understanding of user interactions and offers informative codebooks for researchers and developers interested in building similar mental health support systems. Furthermore, it suggests data-driven hypotheses regarding helpful reframing types and explores the potential integration of AI and machine learning to enhance cognitive reappraisal interventions.

The following article [7] provides a brief overview of a set of design guidelines for technology-driven solutions in mental health treatment, stemming from existing literature and development projects. These guidelines encompass the Design Process, focusing on collaborative design and access challenges, Design Factors, considering therapeutic models, client-specific factors, and privacy, and the Evaluation Pro-

cess, addressing unique assessment challenges. By referencing real projects, these guidelines aim to aid researchers and practitioners in enhancing the accessibility, engagement, effectiveness, and affordability of mental health support through technology, thereby contributing to the emerging field of Human-Computer Interaction in this domain.
In the research of Rachel Kornfield,[35] they focus on young adults who often experience mental health issues but are reluctant to seek traditional treatment. Instead, they frequently turn to online resources, including mental health self-screeners. To gain insights into this phenomenon, the researchers conducted focus groups with 50 young adults who voluntarily used a mental health screener on an advocacy website. The study aimed to understand (1) why they took the screener, (2) what they expected from it, (3) how they reacted to the results, and (4) what steps they desired to take next.
Author Pawan Suresh stated in their research that[37], recent technological advancements have led to a rise in targeted digital interventions, particularly in the field of mental health services. These interventions involve the use of mental health chatbots, which claim to offer therapeutic care through the application of Natural Language Processing (NLP) techniques. A chatbot, in essence, is a computer program designed to deliver intelligent responses to user input, comprehending natural language through one or more NLP strategies.
In the discussed paper authors mentioned[18] the significance of incorporating mental health considerations in HCI4D (Human-Computer Interaction for Development) research is highlighted. Drawing inspiration from the works of Appadurai and other scholars, the authors emphasize the relationship between aspirations and mental health, noting that the state of an individual's mental health can shape their future goals and aspirations. The paper introduces the aspirations-based design framework and elucidates its three aspects: temporality, embeddedness, and mutability, suggesting that mental health is intertwined with these facets. It underscores that an individual's cultural background, socio-economic status, and stigma around mental health can influence symptom presentation and, in turn, affect how they interact with technology-based interventions. The authors advocate for collaborations between HCI4D practitioners and mental health professionals to design ethically sound and impactful studies. They provide a list of best practices, emphasizing the importance of addressing both structural and individual factors causing mental distress, considering cultural nuances, and prioritizing participant privacy and confidentiality. The paper concludes by highlighting the intersectional nature of mental health and raising several pertinent questions for future exploration in the field of HCI4D.
The paper of Cristina Botella[8] explores the integration of Augmented Reality Exposure Therapy (ARET) in treating cockroach phobia within the mental health domain. By using ARET, the study observed its efficacy in building a therapeutic relationship between the therapist and the client. Results indicated a significant reduction in the patient's anxiety levels, beliefs in catastrophic thoughts, and avoidance behaviors towards the phobic stimulus post-therapy. The study underscores the need for a multidisciplinary approach, emphasizing both HCI (Human-Computer Interaction) and clinical considerations, to ensure that the technology genuinely supports the therapeutic process. While ARET has shown potential, the authors stress the importance of expanding the study to a larger sample and further validating results against control groups for a more comprehensive understanding.

This systematic analysis [20] delves into the literature on depression, anxiety, and bipolar health issues presented over a decade in SIGCHI conference proceedings. The findings emphasize a predominant focus on automated diagnosis and self-tracking within mental health technologies. Despite the growing body of work, there is a limited clinical evaluation of these technologies, pointing to a need for more robust interdisciplinary collaboration between HCI, clinical psychology, and other relevant sectors. The research also underscores the ethical considerations surrounding the participation of individuals with affective disorders, emphasizing the importance of anonymity, consent, privacy, and reflection. Future directions proposed include leveraging the full spectrum of available technologies, designing for empathy and inclusiveness, and promoting ethical practices, particularly when working in clinical settings.
In this article [38], the focus is on the impact of cognitive distortions, defined as erroneous thoughts, on mental health, especially in light of increased mental health challenges due to factors like COVID-19. The article explores the potential of serious games, like the adapted ARCoD, accessible on smartphones and utilizing Augmented Reality, to assess five different cognitive distortions in individuals. The aim is to bridge the gap in mental healthcare accessibility by providing a digital solution. Experimental results indicate that the cognitive distortion levels measured through the game closely match those from an established scale, the Cognitive Distortion Scale (CDS), offering promise as an effective assessment tool.
There are several speech recognition services available in the field of mental health detection. For the comparison of that service, research is being conducted by the author Ricardo Oliveira in their paper[22]. For their research, they took 4 ASR(automatic speech recognition system) services. The services are choices from different vendors. The data is collected from the device recording of the users. For the devices, they choose mobile and laptops. After gathering the data author put general normalization which brings a drastic result of WER(word error rate). Apart from WER, they measure SNR for noise level estimation in the recordings. Based on the parameters the the performance is being evaluated of the services.
In the following paper, [10], mostly discusses the use of technology and computing in the context of mental health. Computer Interaction is actively working on developing technologies to support individuals with these challenges. These technologies include using wearable sensors to monitor sleep patterns and analyzing social media activity to infer mental states. The paper mentions a multidisciplinary workshop where experts from several fields such as researchers, developers, and mental health professionals. They will share their ideas and positions based on the topic which will be through videos, which will be included on the website. Moreover, as a post-workshop, the participants will be invited to submit an extended paper based on the discussions that took place in the workshop which later can be published in the journal.
The major purpose of this study is to offer how post-traumatic stress disorder (PTSD) patients might be helped by using data from fitness trackers like Fitbit[17]. We spoke with mental health professionals to get their opinions on using this information in therapy. This information could potentially aid patients by giving them insights into their symptoms, confirming their experiences, and supporting the development of their therapy, according to providers. They did, however, also express worries and difficulties. They were concerned that the use of this data in mental

health had not received any clinical validation and were dubious of its ability to effectively guide treatment choices. It would take a lot of time and effort to interpret this data, which would take attention away from self-reporting and accepted practices. A major theme was the conflict between seeing this data as "objective" and necessitating subjective interpretation. Providers emphasized the significance of contextualizing this data for the patient and using their therapeutic knowledge to derive actionable insights. The researchers also thought that patients could learn how to grasp and use this information through clinical interactions. Organizational issues were a major barrier because existing procedures were tightly related to conventional data collection techniques. Providers required organizational support and training as well as more clarity on how to incorporate data-driven activities into current practices. Despite the possibility that this data can improve mental health services, providers still face a number of acceptance issues. Ensuring that the integration of this data benefits patients and providers while resolving ethical concerns, requires careful consideration and collaboration among stakeholders.

With a focus on Human-Computer Interaction (HCI), this study [33] examines how technology and mental health care interact. From its early opposition to technological advancements to the current era of digital mental health solutions, it covers the historical history of HCI's involvement in mental health. The study emphasizes the importance of working together among mental health professionals, academics, policymakers, and developers while highlighting the possibilities of incorporating digital technologies into clinical care. The study draws attention to issues including the dearth of empirical data supporting web-based interventions and the significance of human aspects in the creation of user-friendly, moral, and efficient AI-driven mental health tools. It also looks at how cutting-edge technologies like virtual reality and intense video games could be used to treat mental health issues. The research recommends that HCI concepts be better included in technical developments for digital mental health in order to improve quality, safety, and usability while addressing systemic problems with mental health treatment.

The author's objectives in this paper are [19] to comprehend the experiences of people with complex health needs, such as mental health problems, and how these affect their day-to-day activities. The study emphasizes how psychosocial disorders like anxiety and depression have a substantial negative impact on people's well-being and frequently co-occur with physical health issues. The study highlights the necessity for comprehensive assistance systems and emphasizes the significance of adopting a holistic strategy to support people who are dealing with numerous disabilities. The research suggests a chance to combine a social model perspective with current medical treatments, even if medical areas have advanced in treating psycho-social disorders. As a result, assistive technology may be created to empower people and put their needs and experiences at the center of technical breakthroughs, rather than just treating symptoms. In the end, this strategy seeks to improve the general well-being of people with psycho-social disabilities and advance a more accepting and encouraging society.

In light of the worldwide increase in mental disorders, this study [4] addresses the urgent dilemma of delivering readily available, interesting, and reasonably priced mental health care. It draws attention to the possibility of technology as a remedy, particularly for talk-based mental health interventions (MHIs). The paper examines several theoretical perspectives on mental health treatment as well as the scant

prior research on technology's function in this area. It highlights how important it is for human-computer interaction (HCI) academics to be involved in creating technologies that improve access, lessen stigma, and foster greater participation in mental health treatments. The study highlights the need for close cooperation between HCI experts and mental health practitioners by outlining important hurdles, such as access restrictions and ethical issues. It suggests design principles and a cooperative development paradigm. Additionally, flexibility is recognized as being crucial for developing client-centered technology. In order to alleviate the worldwide burden of mental disease, the paper serves as a platform for further study and encourages HCI researchers to contribute to the ongoing initiative to enhance mental health care through technology.
In particular, when parents are preoccupied with work or other obligations, this study [36] sought to identify a method to assist both parents and children who are experiencing mental health issues. Utilizing the "design thinking" methodology, they gathered concepts based on what they had discovered from earlier studies. They produced a prototype, akin to a sampling version, and requested testers. The outcomes were positive; users found it simple to use, and parents believed it enabled them to monitor the mental health of their children. They intend to eventually improve it by turning it into a mobile application. In addition, they want to enable large families and add more capabilities like speech recognition. The addition of a video call option was also considered. Therefore, the focus of this study is on employing technology and innovative ideas to make life easier for parents and kids when it comes to mental health.
Yngve Lamo presents a conceptual framework of how Natural Language Processing (NLP) may be used to develop a customized online mental health treatment programme[24]. They discovered that the inflexibility of current systems frequently results in user attrition and decreased adherence. They created a technique called "Depression2Vec" to extract depression symptoms from the writing of patients in order to address this. By employing patient-authored text to modify mental health therapies, they intended to fill a vacuum in earlier studies. The study found certain drawbacks, including the fact that the algorithm's performance depends on how rich the text input is and that there may have been assessment biases. They also pointed out that the program ignored sophisticated linguistic constructions and made assumptions about the material written by patients. They emphasized that their strategy delivers personalized and interesting therapy experiences, which may be especially helpful for those with minor mental health difficulties. Additionally, it can aid therapists in spotting early signs of severe depression. Future work will handle complicated language structures, include domain experts, and increase program accuracy. Overall, this study establishes the groundwork for more flexible and efficient internet-based mental health therapies.
The study article by Ka I Pun [16] is part of the INTROMAT project, which aims to enhance mental and neurological healthcare through technology. It addresses various major field issues. The first solution to heterogeneous healthcare data is a cloud-based system combining SOA and HL7 FHIR standards for consistent data interchange. Second, it offers a self-assessment mobile app to make mental health more accessible and private for patients, reducing stigma. The report acknowledges worldwide mental health challenges and the necessity for ongoing monitoring and treatment. Web-based psychotherapy, particularly cognitive behavioral therapy, is

promising due of its cost-effectiveness and flexibility. The report stresses the necessity of tailoring treatments to individual patients and advocates using wearable sensors to generate individualized, evidence-based treatments. Mobile apps, virtual reality, and voice assistants could administer these therapies, making mental healthcare more patient-centric and successful. Recent advances in natural language processing (NLP) have shown promise for early mental disorder diagnosis and proactive management. Mental illness is common and affects society. NLP helps computers interpret text data from social media, interviews, and clinical notes to identify mental health issues.

This comprehensive paper [39] review of over a decade's worth of research reveals several key insights. While both traditional machine learning and deep learning methods have been used, deep learning, particularly using advanced techniques like neural networks, has shown better performance. However, challenges persist, such as limited and biased annotated data, model instability, and the need for interpretability in NLP models. Future research directions include exploring semi-supervised and unsupervised learning, incorporating ethical considerations, and enhancing model interpretability. The ultimate goal is to improve mental health diagnosis and empower clinicians with reliable, understandable, and privacy-respecting tools for early intervention and support.

According to this paper [32], the criticality of timely intervention in mental health disorders, particularly focusing on the duration of untreated psychosis (DUP), is defined as the time between first psychotic symptoms and treatment initiation. Lengthier DUPs often lead to poorer outcomes, necessitating comprehensive research on disease trajectories. Electronic Health Records (EHRs) offer a valuable resource for such research, with psychosis onset data often embedded in unstructured text. To unlock this information, Natural Language Processing (NLP) techniques are employed, addressing the challenge of diverse mentions and contexts for disease onset. The study proposes an NLP approach that annotates mental health EHRs, models the problem as a paragraph classification task, and aggregates relevant paragraphs to rank likely disease onset dates. The method is demonstrated on a corpus and applied at scale, facilitating the estimation of DUP for a substantial patient cohort.

The Authors aimed[12] to utilize natural language processing (NLP) to create a suite of language models capable of capturing crucial symptoms of severe mental illness (SMI) from clinical text, facilitating the secondary use of mental healthcare data for research purposes. Using the Clinical Record Interactive Search (CRIS) data resource, the research focused on developing and validating information extraction applications to ascertain SMI symptoms from routine mental health records. The electronic records were obtained from a significant mental healthcare provider serving a substantial geographic catchment in south London, UK. A total of 50 SMI symptoms were identified for extraction, broadly categorized into positive, negative, disorganization, manic, and catatonic subgroups. The study successfully extracted data for 46 symptoms with a median F1 score of 0.88, providing valuable insights into the distribution of these symptoms across patients with SMI and those with non-SMI diagnoses based on a corpus of discharge summaries.

The study [25] employs text mining and natural language processing (NLP) techniques, particularly topic modeling with automated topic labeling, to analyze persuasive strategies used in 100 mental health apps based on user reviews. Focusing on the primary task support category of the Persuasive Systems Design (PSD) framework, the researchers used the Latent Dirichlet Allocation (LDA) algorithm and semantic attributes to deconstruct these strategies. Their findings indicate that self-monitoring is the most commonly employed persuasive strategy, followed by personalization and tailoring, as well as simulation and rehearsal. Conversely, reduction and tunneling were the least used strategies. The study also compares its results with those obtained through manual coding, revealing significant similarities. Future research plans involve expanding the study to include a larger sample of mental health apps and exploring negative reviews to assess the impact of persuasive strategies on the overall user experience, ultimately proposing design solutions to address identified gaps.

Dr Gavin Doherty and his research team conducted a study [15] to explore the feasibility and appropriate design of mobile applications for engaging pregnant women in self-reporting their well-being and depression. They developed an application named BrightSelf, involving pregnant women, healthcare professionals, and public health researchers in its development and deployment. The application allowed women to report on various aspects of their mood, energy, rest, enjoyment, and worry both in the moment and retrospectively. The findings of the study indicate that the application effectively engaged a diverse population of pregnant women, regardless of demographic characteristics, and facilitated longitudinal, momentary, and retrospective data collection. Notably, it helped overcome stigma related to mental health issues, supported disclosure, and fostered trust between patients and midwives. The study highlighted the importance of simple and efficient interaction design, as well as appropriate notification protocols. Overall, the research conducted by Dr. Gavin Doherty and his team demonstrated the potential of mobile applications in antenatal mental health screening and care, emphasizing the need for user-centric design in public health technology solutions. However, some challenges related to notification frequency were identified as areas for improvement.

Examining the effects of using freemium design techniques in mental health (MH) applications was the focus of this extensive study. This research [34] endeavor employed user evaluations and expert audits to investigate the adverse effects linked to the implementation of freemium models in mental health applications. The study findings indicate that individuals with mental health vulnerabilities, especially those experiencing crisis situations, frequently face difficult choices when deciding between getting necessary care and facing unanticipated financial burdens. These individuals often experience recurring and emotionally burdensome requests for upgrades, which exacerbate their distress during crucial periods. In addition, the presence of ambiguous application descriptions may give rise to unsuitable interventions or unanticipated financial burdens. Moreover, the temporal constraints inherent in freemium models might potentially hinder the efficacy of therapies, rendering them partial or subject to interruptions. While a considerable percentage of users encounter favorable results with mental health applications, a notable number encounter unfavorable effects, highlighting the need for design methods that prioritize the needs and preferences of users in this particular context. The research brings attention to a notable concern regarding the possibility of exploiting users' weaknesses in times of crisis. It suggests that the freemium model, albeit unintentional, could potentially worsen mental health difficulties. The popularity of freemium models in a wide range of goods is underscored by the authors, who argue for a reevaluation of their implementation in the context of mental health applications, which are considered

to be a sensitive domain.
In order to improve young people's online help-seeking behavior for mental health difficulties, Claire Pretorius and her co-authors undertook a study. In order to accomplish this objective, the researchers [26] utilized personas and included well-established ideas related to help-seeking and psychology. The study employed two primary methodologies: a survey was conducted to gain an understanding of the online assistance objectives of young individuals, and co-design workshops were utilized to generate design recommendations based on personas informed by empirical data. The results of the study emphasized the significance of offering chances for connectivity, reliable and easily accessible information, customization with consideration for anonymity, and timely support alternatives in online services for mental health. Nevertheless, the study acknowledged certain constraints, such as the utilization of a non-clinical sample and the possibility of cultural biases. These limitations underscore the necessity for additional investigations and the amalgamation of help-seeking theories with Information Science perspectives. This integration would provide a more profound understanding of how young individuals navigate online mental health resources.
Natural language processing (NLP) from psychotherapy notes was used to enhance suicide prediction models in the study [29]. Participants in the cohort were Veterans Health Administration (VHA) patients who received a post-traumatic stress disorder (PTSD) diagnosis between 2004 and 2013. Through the use of a case-control design, cases—those who took their own lives within a year of being diagnosed—were matched with controls, or people who lived. A 5:1 nearest-neighbor propensity match was used to select controls using the VHA's structured suicide prediction model based on Electronic Medical Records (EMR). Sentiment analysis and Cognition Engine, a Python-based NLP program, were used to examine psychotherapy notes. The predicted accuracy was evaluated by computing the area under the curve (AUC) using machine-learning methods employed in the investigation. The findings indicated that, especially for patients receiving prolonged treatments, NLP-derived variables somewhat improved prediction accuracy (AUC = 0.58). Predictive precision was, however, constrained by the small sample size. This new way of tracking suicide risk over time and maybe grouping patients into subgroups with different risk sensitivity is presented in the paper. Beyond the present structured EMR-based suicide prediction model used by the VHA, it suggests that utilizing NLP-derived variables from psychotherapy notes has extra predictive value. Replicating the study with a wider, non-PTSD-specific sample is something the authors strongly recommend.

Chapter 6

Dataset Description

6.1 Machine Learning for Mental Health Dataset

Dataset Overview:
The provided dataset [13] appears to be related to mental health survey responses from individuals in various countries. Each row in the dataset represents a survey response from an individual, and the dataset contains several attributes or columns related to the respondents' demographics, mental health history, workplace-related factors, and attitudes toward mental health.

Dataset Attributes:
Timestamp: The date and time when the survey response was recorded. Age: The age of the respondent. Gender: The gender of the respondent. Country: The country in which the respondent is located. State: The state or region within the respondent's country. Self-Employed: Whether the respondent is self-employed (Yes/No). Family History: Whether the respondent has a family history of mental health issues (Yes/No). Treatment: Whether the respondent has received treatment for mental health issues (Yes/No). Work Interfere: How often mental health issues interfere with the respondent's work (e.g., Often, Rarely). No. of Employees: The size of the respondent's workplace in terms of the number of employees. Remote Work: Whether the respondent has the option to work remotely (Yes/No). Tech Company: Whether the respondent works in a tech company (Yes/No). Benefits: Whether the respondent's employer provides mental health benefits (e.g., Yes, No, Don't know). Care Options: The availability of mental health care options at the workplace (e.g., Yes, No, Not sure). Wellness Program: Whether the respondent's workplace offers a wellness program (Yes/No). Seek Help: Whether the respondent would feel comfortable seeking help for mental health issues (Yes/No). Anonymity: Whether the respondent's anonymity is protected when seeking mental health treatment (Yes/No). Leave: The ease of taking medical leave for mental health reasons (e.g., Somewhat easy, Very difficult). Mental Health Consequence: Whether the respondent believes that discussing mental health issues would have negative consequences at work (Yes/No). Phys Health Consequence: Whether the respondent believes that discussing physical health issues would have negative consequences at work (Yes/No). Coworkers: Whether the respondent would be comfortable discussing mental health issues with coworkers (e.g., Some of them, No). Supervisor:

Whether the respondent would be comfortable discussing mental health issues with their supervisor (e.g., Yes, No). Mental Health Interview: Whether the respondent has been asked about their mental health in a job interview (e.g., Yes, No). Phys Health Interview: Whether the respondent has been asked about their physical health in a job interview (e.g., Yes, No). Mental vs. Physical: Whether the respondent perceives mental health issues as being taken as seriously as physical health issues at work (e.g., Yes, No). Obs Consequence: Whether the respondent believes there would be negative consequences if a mental health issue is revealed (e.g., Yes, No). Comments: Additional comments or remarks provided by the respondents.

Dataset Insights: The dataset offers a comprehensive view of individuals' attitudes and experiences related to mental health in the workplace. It encompasses a diverse demographic range, with respondents from various countries, ages, and gender identities. Key insights include a significant portion of respondents reporting a family history of mental health issues and having received treatment themselves. The dataset also sheds light on how often mental health issues interfere with work and the varying attitudes toward seeking help, ranging from comfort to fear of negative consequences or lack of anonymity. It provides information on workplace-related factors like company size, remote work options, and the availability of mental health benefits and wellness programs. Additionally, some respondents have been asked about their mental health in job interviews, highlighting the intersection of mental health and employment. The "Comments" column further enriches the dataset by offering qualitative context and personal experiences related to mental health in the workplace. This dataset serves as a valuable resource for gaining insights into the complex dynamics of mental health within work environments.

6.2 AIML and Scientific Charts Dataset

Dataset Overview: The dataset [40] provided for this research paper is designed to investigate and enhance stress management and mental wellness among undergraduate students in Bangladesh. The dataset contains information collected from 469 students and includes various attributes related to students' mental well-being, lifestyle, and academic choices. The data was collected at a specific point in time, with timestamps provided for each entry.

Dataset Attributes:
Timestamp: Date and time when the data entry was recorded.
Gender: The gender of the student (e.g., Male, Female).
Age: The age of the student.
Department: The department or field of study the student is enrolled in.
Are you happy with your department's work area: Whether the student is satisfied with their department's work environment (e.g., Yes, No).
Why did you choose your department work area: The reason behind the student's choice of their department's work area.
Current year you are studying in: The academic year the student is currently enrolled in.
CGPA: The student's current Cumulative Grade Point Average.

Are you having proper sleep every day: Whether the student is getting adequate sleep daily (e.g., Yes, No).
How much time are you sleeping every day: The average amount of time the student sleeps each day.
Are you getting a good food diet every day: Whether the student is satisfied with their daily diet (e.g., Yes, No).
What is your screen time: The total amount of time the student spends on screens.
On what you spend your screen time more: The primary activity the student engages in during their screen time.
From where you are getting stress: The source or trigger of stress for the student.
When you are stressed more: The circumstances or situations when the student experiences more stress.
What will you like to do when you are stressed: How does the student prefer to cope with stress.
How did you feel during the COVID-19 pandemic period: The student's emotional state during the COVID-19 pandemic.
Can you concentrate on your work when you are stressed: Whether the student can concentrate on their tasks when they are stressed (e.g., Yes, No).

Dataset Insights:
A wide range of undergraduate students from different academic backgrounds, ages, and genders are included in the dataset.Students have different motives for selecting their departments and differing levels of satisfaction with the work environment within them.Because of the differences in their academic backgrounds, students' CGPAs also differ.The students also differ in their sleep habits and levels of diet satisfaction.The dataset records students' preferences for screen time as well as their experiences with stress.It also contains details about students' mental states during the COVID-19 pandemic, how they manage stress, and how well they focus under pressure. There are 17 characteristics and 469 entries in the dataset.This dataset can be a useful tool for figuring out what influences stress and mental health among Bangladeshi undergraduate students, which can help with the creation of supportive networks and interventions that work. The connections between these characteristics and students' mental health can be better understood through additional research and modeling.

6.3 Student Mental Health Dataset

Dataset Overview: This dataset [41] was collected through a Google Forms survey aimed at investigating the impact of mental health on Bangladeshi undergraduate students' academic achievement. It attempts to offer insights into the mental health issues, demographic data, and academic standing of students as measured by their cumulative grade point average (CGPA). The dataset enables investigation of the association between students' CGPA and mental health, as well as comprehension of the treatment-seeking behavior of the participants.

Dataset Attributes: The dataset consists of several attributes:

Dataset	Related Parameters
Machine Learning for Mental Health	1. Gender 2. Treatment 3. Family History 4. Seek Help 5. Anonymity Preference 6. Mental Health Consequences
AIML and Scientific Charts	1. Gender 2. Age 3. Screen Time 4. Stress Source 5. When stressed more 6. Like to do when stressed 7. Affect of stress on concentration
Student mental health	1. Gender 2. Age 3. What is your course? 4. Current CGPA 5. Do you have anxiety? 6. Do you have depression? 7. Do you have panic attack? 8. Seek any treatment

Table 6.1: Related Parameters of the Datasets

Timestamp: The date and time when the survey response was recorded. Choose your gender: Categorical data representing the gender of the respondent. Age: Numerical data representing the age of the respondent. What is your course?: Categorical data indicating the academic course or major pursued by the student. Your current year of Study: Categorical data specifying the current academic year or level of the student. What is your CGPA?: Ordinal data categorizing the Cumulative Grade Point Average (CGPA) into predefined ranges. Marital status: Binary data indicating the marital status of the respondent. Do you have Depression?: Binary data reflecting whether the student has been diagnosed with depression. Do you have Anxiety?: Binary data indicating whether the student has been diagnosed with anxiety. Do you have a Panic attack?: Binary data indicating whether the student has experienced panic attacks. Did you seek any specialist for treatment?: Binary data indicating whether the student sought specialist treatment for mental health issues.

Dataset Insight The dataset offers a comprehensive view of the mental health status and academic performance of undergraduate students in Bangladesh. It encompasses a diverse range of students in terms of gender, age, academic year, and CGPA. Notably, it provides insights into the prevalence of mental health issues such as depression, anxiety, and panic attacks among these students, shedding light on their mental well-being. Furthermore, the dataset reveals whether students sought specialist treatment for their mental health concerns. There are 102 entries in the dataset and have 11 features.

Chapter 7

Methodology

7.1 Dataset Exploration and Analysis:

As part of our comprehensive dataset research and analysis, we undertook a thorough investigation of publically accessible datasets concerning mental health attitudes, stress management, and academic achievement among undergraduate students. Throughout this procedure, a thorough assessment was conducted to determine the appropriateness of these datasets in relation to our study goals.

7.2 Data Preprocessing and Model Train:

After completing the phase of collecting the dataset, a series of preprocessing activities were undertaken to appropriately prepare the data for the training process. Upon initial examination of the dataset, our primary attention was directed towards addressing the issue of missing values, specifically in the age variable. The age numbers that were not provided were estimated by utilizing a Python dictionary, which was based on the relevant year of research. In addition, we optimized the dataset by eliminating unnecessary columns, such as timestamps, status information, and irrelevant comments. Following this, we conducted encoding in order to convert the processed data into a format that is appropriate for modeling. After obtaining the preprocessed data, we proceeded to divide it into two sets such as a training set and a testing set. The training set consisted of 80% of the data, while the testing set contained the remaining 20%. This facilitated the training and evaluation of diverse machine learning models on the partitioned data. Ultimately, a thorough examination was undertaken to assess the overall effectiveness of the models, with the aim of extracting meaningful observations from the dataset.

7.3 Survey Questionnaire Design:

Due to the insufficiency of already available datasets in relation to our study goals, we embarked on the meticulous development of a customized survey questionnaire. The present bespoke questionnaire was meticulously crafted, by utilizing the idea gained from gathered dataset analysis and also using the HCI methods. The survey questions have been carefully designed to cover a wide range of relevant topics. The subjects encompassed in this study consist of an examination of mental health disorders, the influence of scholastic stressors, the efficacy of diverse coping strategies, and perspectives regarding technology-driven interventions. The purpose of developing this customized survey is to gather data that will facilitate a comprehensive comprehension of the distinct obstacles encountered by undergraduate students in Bangladesh in relation to stress management and mental well-being.

7.4 Consulting with Experts:

As a critical step in our research process, we intend to collaborate with mental health professionals in the coming stages. Their expertise will play a pivotal role in the review and refinement of our survey questions. By engaging these experts, we aim to enhance the precision and sensitivity of our questionnaire to ensure that it effectively captures the nuanced experiences and perspectives of undergraduate students in Bangladesh. Furthermore, their input will contribute to maintaining the highest ethical standards throughout our research, ensuring that the well-being and privacy of participants are carefully safeguarded. This collaborative effort underscores our commitment to conducting a comprehensive and responsible study on stress management and mental wellness among undergraduate students.

7.5 Data Collection :

Informed by the guidance of mental health experts and the careful refinement of our survey questionnaire, we are now ready to progress to the data collection phase of our research. Our methodical approach involves the administration of this tailored survey to a meticulously selected sample of undergraduate students in Bangladesh. To ensure accessibility and user-friendliness for our participants, we have opted for Google Forms as our preferred platform for data collection. Google Forms not only offers a seamless and efficient means for participants to share their invaluable perspectives on stress management and mental wellness but also provides the flexibility needed to incorporate various data collection methods and techniques.

Using both qualitative and quantitative research methods, we will utilize a snowball sampling strategy to find and identify possible participants. This could involve informal discussions on social media and messaging apps, as well as surveys and interviews done using Google Forms. To explore the complex experiences and insights of participants, we will use in-depth qualitative interviews as part of our qualitative research methods. We hope to obtain high-quality data by using these thorough methods of data collection, which will provide a strong basis for our research's next phases, which will include rigorous analysis and the creation of insightful findings. By using many strategies, we can make sure that we include a wide variety of viewpoints and experiences about stress management and mental wellness among Bangladeshi undergraduate students, which will enhance the breadth and depth of our research findings.

7.6 Data Labeling :

Data labeling is a crucial step in our research process that comes after the completion of data gathering via our carefully planned survey. We intend to use the knowledge of mental health specialists to guarantee the accuracy and consistency of our dataset. In order to classify and interpret the survey replies, their participation in the data labeling process is essential. This stage is crucial to our research because it lays the groundwork for accurately predicting stress levels and mental health issues among Bangladeshi undergraduate students. Through this kind of professional collaboration, we hope to attain the highest standards of data credibility and correctness, which will ultimately strengthen the validity of our study findings and insights.

7.7 Model Testing and Evaluation :

After the data labeling stage is finished, we plan to use a variety of sophisticated models, such as Natural Language Processing (NLP) and Human-Computer Interaction (HCI) methods, to fully address the difficulties with enhancing stress management and mental health among Bangladeshi undergraduate students. Our research collection includes the K-Nearest Neighbors (K-NN) method as one of its models. This machine learning method is essential to our research because it makes it easier to identify and group kids who have comparable stress or mental health issues. It improves the state of mental well-being overall by enabling the creation of peer support networks and customized therapies. Furthermore, K-NN plays a key role in the development of HCI user interfaces that adjust to the specific needs of each user, including their stress levels and mental health conditions.

Another key model in our research is Logistic Regression, which aids in predicting the probability of students experiencing mental wellness issues based on various factors. Logistic regression's interpretability and model validation metrics provide valuable insights into the factors contributing to mental wellness challenges, guiding the development of targeted interventions.

The Random Forest ensemble machine learning method is another powerful tool at our disposal. By combining decision trees and addressing issues such as over-fitting and missing data, Random Forest enhances the accuracy of predictions. Its interpretability and ability to clarify feature importance contribute to a comprehensive understanding of stress management and mental well-being among undergraduate students.

Moreover, in the context of the research paper titled "Enhancing Stress Management and Mental Wellness in Bangladesh for Undergraduate Students through NLP and HCI" gradient boosting can play an essential role. The software provides functionalities for predictive modeling, feature selection, text categorization, and personalized recommendation systems. Additionally, it has the benefit of producing findings that can be easily understood and enhances prediction accuracy by utilizing ensemble techniques. Therefore, it can be argued that it is an essential resource for promoting stress management and improving the psychological welfare of undergraduate students in Bangladesh.

In addition, the incorporation of a decision tree into our research has numerous

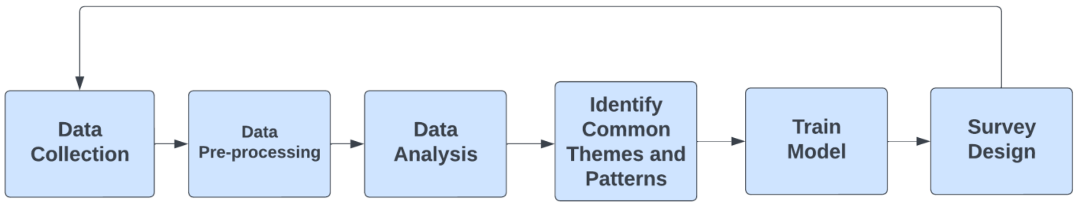


Figure 7.1: Methodology Pipeline

advantages. This study aims to facilitate the identification of crucial stress-related factors, the selection of pertinent variables from the fields of Natural Language Processing (NLP) and Human-Computer Interaction (HCI), the prediction and classification of stress levels, the evaluation of intervention efficacy, the prioritization of critical factors, the personalization of interventions, the enablement of continuous monitoring, and the simplification of complex decision-making processes for stakeholders. These endeavors collectively have the potential to greatly improve the overall well-being of students in Bangladesh.

In our evaluation process, these models will be rigorously assessed for their capacity to predict mental health conditions, stress levels, and other pertinent factors among undergraduate students in Bangladesh. Additionally, their performance will be compared with models that have demonstrated excellence in similar datasets. This comprehensive approach to model testing and evaluation will underpin our research's robustness and contribute valuable insights to the promotion of mental wellness and stress management among undergraduate students.

Chapter 8

Model Description

In our research, initially, we considered using BERT, RoBERTa, and DistilBERT models. However, based on the complexity and scale of our research we figured out that these models won't be efficient. For this reason, we used the following models for our research.

8.1 K-Nearest Neighbours

The K-Nearest Neighbors (K-NN) algorithm is a machine learning technique used [3] for the classification and prediction of data points. It operates by determining the proximity of a data point to other data points within a specified dataset. In the context of the study, work focused on augmenting stress management and promoting mental well-being among undergraduate students in Bangladesh through the utilization of Natural Language Processing (NLP) and Human-Computer Interaction (HCI), the K-Nearest Neighbors (K-NN) algorithm can serve as a valuable tool. Through the utilization of the K-Nearest Neighbors (K-NN) algorithm, it becomes possible to discern and categorize students who exhibit comparable degrees of stress or mental well-being. This facilitates the development of customized interventions and the establishment of peer support networks. Moreover, the K-Nearest Neighbors (K-NN) algorithm has the potential to support individualized recommendations for students who are facing difficulties by leveraging the knowledge gained from their closest peers. Within the field of Human-Computer Interaction (HCI), the utilization of the K-Nearest Neighbors (K-NN) algorithm can be advantageous in the development of user interfaces that possess the capability to adapt to the unique requirements and preferences of individual users. This adaptation process encompasses the consideration of factors such as the users' stress levels or mental health state. In order to enhance its effectiveness, it is imperative to do data preprocessing, choose a suitable distance measure, and ascertain the ideal value of K by empirical investigation. This may be supplemented by incorporating additional techniques from the fields of natural language processing (NLP) and human-computer interaction (HCI) to adopt a holistic methodology.

sectionLogistic Regression Another model we will be using in our research is logistic regression [5]. Logistic regression serves as a pivotal analytical tool in our research endeavor aimed at enhancing stress management and mental wellness among undergraduate students in Bangladesh. This statistical method enables us to predict the probability of students experiencing mental wellness issues based on various factors like demographics, stress levels, and lifestyle variables. By training a logistic regression model on historical data, we can identify at-risk students and determine the most influential factors contributing to their mental wellness challenges. Logistic regression's ability to be interpreted, its model validation metrics, and its ability to choose features make it an important tool for guiding the development of targeted interventions and informing policymakers about the importance of NLP and HCI-enhanced strategies to promote mental health. Coupled with NLP and HCI techniques, logistic regression helps us leverage textual and interaction data to augment the model's predictive power and gain a comprehensive understanding of stress and mental wellness dynamics among undergraduate students in Bangladesh (Hastie, Tibshirani, & Friedman, 2009).

8.2 Random Forest

The incorporation of the Random Forest ensemble machine learning method can help greatly enhance the feasibility of our research. The Random Forest algorithm functions by combining several decision trees,[2] each of which is trained on random subsets of both data and features. This approach improves the accuracy of predictions and reduces the occurrence of overfitting, as described by Breiman (2001). The tool's strong resilience, ability to clarify the importance of features, and high accuracy in predicting outcomes make it valuable in addressing the complex dimensions of stress management and mental well-being among undergraduate students. Furthermore, this technique provides interpretability by facilitating the display of individual decision trees within the forest, hence enhancing the understanding of prediction reasoning. Additionally, the Random Forest algorithm demonstrates proficient handling of missing data, which is a crucial skill in the context of managing real-world datasets (Liaw & Wiener, 2002). By integrating the Random Forest algorithm with Natural Language Processing (NLP) and Human-Computer Interaction (HCI) techniques, a comprehensive model may be developed to effectively tackle the intricate challenges associated with stress management and the development of mental well-being. This model holds the potential to make a significant contribution to the overall well-being of undergraduate students in Bangladesh.

8.3 Gradient Boost

By employing Gradient Boosting [1], a powerful ensemble machine learning technique, it is possible to significantly improve our research article. Gradient Boosting is a machine learning technique that follows a sequential learning approach. It aims to enhance predictions by iteratively constructing decision trees that rectify the errors made by previous models (Friedman, 2001). The proposed approach involves the utilization of gradient descent to optimize a pre-defined loss function. Additionally, it offers the flexibility to incorporate a shrinkage parameter, which can enhance the resilience of the model. This methodology presents numerous benefits, such as a high level of predictive precision, the ability to evaluate the importance of features, resistance to overfitting, and the capacity to capture non-linear associations within data. These attributes make it particularly suitable for comprehending and forecasting stress management and mental wellness factors among undergraduate students. By incorporating the techniques of Gradient Boosting into the domains of Natural Language Processing (NLP) and Human-Computer Interaction (HCI), our research endeavors can leverage its inherent capabilities to reveal intricate observations and construct a precise model specifically designed to address the distinctive obstacles encountered by the target population residing in Bangladesh.

8.4 Decision tree

Decision trees [9] facilitate the selection of crucial features, such as linguistic patterns from students' expressions and behavioral cues from HCI interactions, identifying indicators associated with stress and mental well-being. Moreover, decision trees can be employed to develop a classification model that predicts varying stress levels based on the identified features. This enables the categorization of students into different stress severity levels, allowing for tailored interventions and support strategies. The models can further guide the creation of personalized recommendations, suggesting appropriate stress management techniques and resources tailored to each student's profile. By integrating decision trees into an interactive HCI system, students can navigate through a series of adaptive questions or interactions, aiding them in recognizing stressors and suggesting suitable actions. Additionally, HCI principles can be applied to design a user-friendly interface, enhancing the overall user experience during stress assessment and management. Continuous refinement and updates to the decision tree models based on real-time data and user feedback ensure the system's adaptability and effectiveness in addressing evolving stress patterns and student needs.

Chapter 9

Preliminary Analysis

Throughout our academic endeavor to enhance stress management and mental wellness among undergraduate students in Bangladesh through the utilization of Natural Language Processing (NLP) and Human-Computer Interaction (HCI), and to gain a deeper understanding of the intricate relationship between these technological approaches and mental health, we meticulously explored existing datasets relevant to our research objectives. While we encountered three datasets closely associated with our goals, it became apparent that these datasets, while valuable, did not entirely align with the specific requirements of our study. In light of these constraints, we made a strategic decision to conduct our own survey, tailored to gather data precisely targeted toward our research objectives. This proactive approach ensures that our dataset will be uniquely suited to our research, allowing us to provide meaningful insights into the intersection of technology, stress management, and mental wellness for undergraduate students in Bangladesh. Through this research initiative, we aim to make a significant contribution to the advancement of this critical domain.

In this discussion, we will examine the datasets that were previously investigated and emphasize their strengths and weaknesses.

The Mental Health Attitudes and Disorders Dataset (MHADD) [13] is a comprehensive collection of data gathered through a 2014 survey, focusing on mental health prevalence and attitudes. It encompasses 1,259 items across 24 features, providing insights into mental health, demographics, and workplace-related factors, though it lacks specific machine learning-oriented questions.

The AIML and Scientific Charts Dataset [40] focuses on stress management and well-being among undergraduate students in Bangladesh, featuring data from 469 students covering aspects like gender, academic performance, and COVID-19-related emotional states.

The Student Mental Health Dataset[41], collected via Google Forms, examines the academic and mental health aspects of undergraduate students in Bangladesh. It includes 102 entries with 11 features, shedding light on mental health conditions, treatment-seeking behavior, and other attributes. These datasets are valuable resources for research on student well-being and interventions in Bangladesh.

In Dataset of Machine Learning for mental health [13], a variety of machine learning techniques were employed to analyze the data, encompassing Logistic Regression, K-Nearest Neighbors (KNN), Random Forest, and Decision Tree. The Logistic Regression model achieved an accuracy rate of 79%, whilst the K-Nearest Neighbors (KNN) model exhibited slightly superior performance with an accuracy rate of 80%.

Dataset	Applied Model	Accuracy
Machine Learning for Mental Health	1. Logistic Regression 2. K-nearest Neighbours (KNN) 3. Random Forest 4. Decision Tree	1. 79% 2. 80% 3. 81% 4. 80%
AIML and Scientific Charts	-	-
Student mental health	1. Logistic Regression 2. Decision Tree 3. Gradient Boosting 4. Random Forest	1. 76% 2. 100% 3. 100% 4. 95%

Table 9.1: Applied Models on the Datasets

The Random Forest model demonstrated a little superior accuracy rate of 81%, while the Decision Tree model also exhibited strong performance, achieving an accuracy of 80%.

In the Student mental health dataset [41], a distinct set of algorithms was employed. The algorithms are Logistic Regression, Decision Tree, Gradient Boosting and Random Forest. The accuracy of Logistic Regression was found to be 76%, whereas both Decision Tree and Gradient Boosting attained a flawless accuracy of 100%. In this particular situation, the Random Forest algorithm achieved an accuracy rate of 95%. The result using both datasets is shown in Figure 9.1

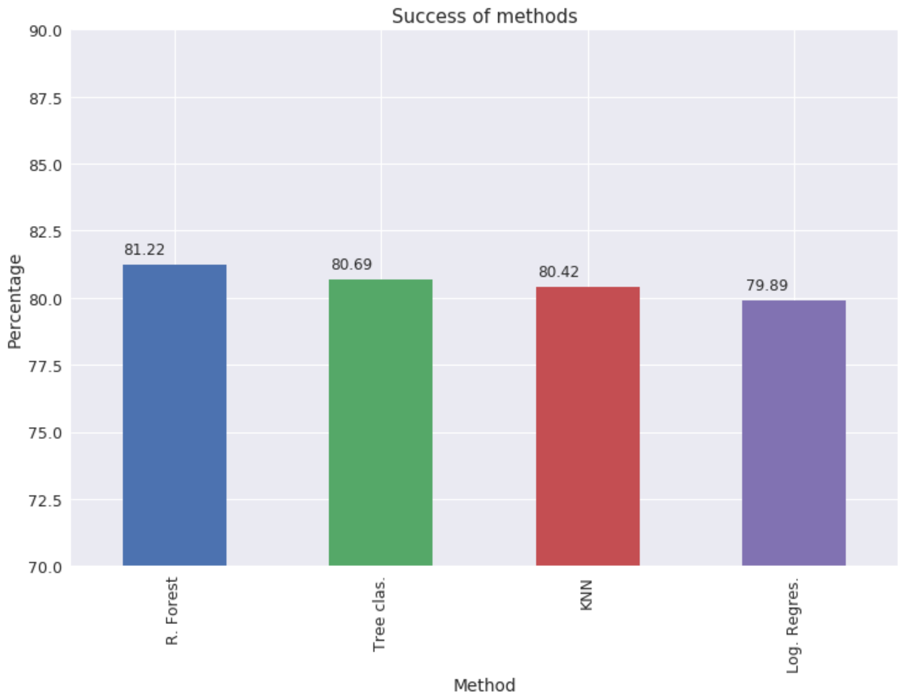
In brief, these datasets provide significant insights into different dimensions of mental health, attitudes, and experiences across diverse populations. But in our research, our objective is to identify the mental health issues and provide a solution based on the problem. The gathered datasets have the basic information about different mental issues but based on the information it is not possible to provide a qualitative solution. Moreover, the gathered datasets are relatively small in the perspective of our research. Apart from all the explored datasets, there isn't much data available on mental health.

To fulfill the goal, our research endeavour involved the development of a tailored dataset via a survey in order to gain a more profound comprehension of the impact of machine learning on mental health. The survey will be based on a questionnaire which will be created by following the analysis of the gathered datasets. and it will be conducted on undergraduate students. After gathering the data from the survey it will be verified through professionals to make the data trustworthy. Also, the immediately gathered dataset info will be provided as a weight to the models for pre-training.

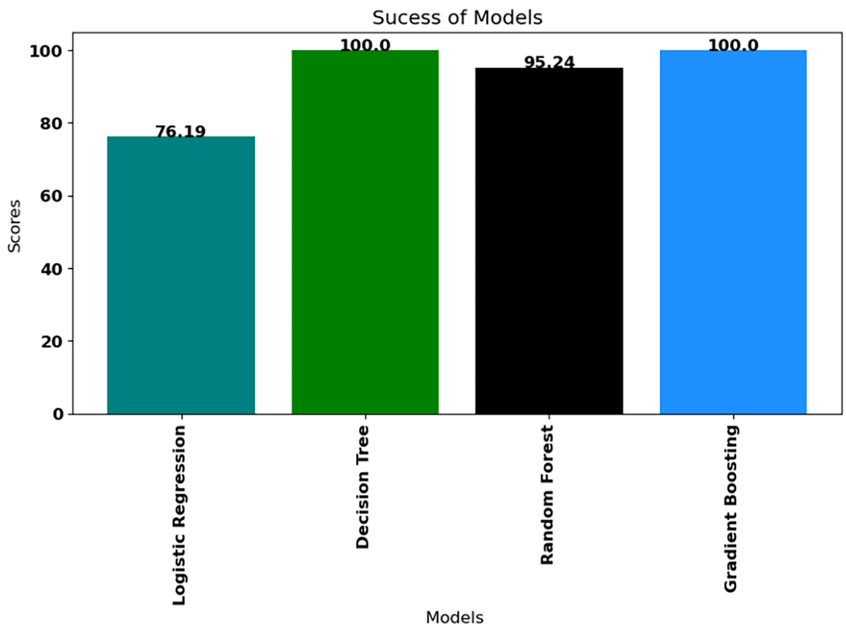
9.1 Survey Questions

For conducting the survey on undergraduate students a set of questions is being prepared. This question will be included in Google Forms.

1. Age: Please indicate your age.



(a) Model run on dataset MLFMH [13]



(b) Model run on dataset SMH [41]

Figure 9.1: Result of Datasets

A. Under 18
B. 18-21
C. 22-25
D. 26-30
E. Over 30

2. Gender: Please specify your gender identity.
A.Male
B.Female
C.Prefer not to say
D.Other (please specify):

Depression:

3. Have you ever been diagnosed with depression?
A. Yes
B. No

4. On a scale of 1 to 5, how often do you experience symptoms of depression (e.g., sadness, loss of interest)?
A. 1 (Rarely)
B. 2 (Occasionally)
C.3 (Sometimes)
D.4 (Frequently)
E. 5 (Constantly)

5. Have you sought professional help or counseling for depression?
A. Yes
B.No

6. How often do you feel stressed due to academic workload?
A. Rarely
B.Occasionally
C. Sometimes
D.Frequently
E. Constantly

7. Do you engage in stress-relief activities (e.g., meditation, exercise)?
A.Yes
B.No

8. On a scale of 1 to 5, how effective are your stress-management strategies?
A.1 (Not effective)
B. 2 (Slightly effective)
C.3 (Moderately effective)
D. 4 (Very effective)
E. 5 (Extremely effective)

9. Do you feel pressure to excel academically?
A. Yes
B. No

10. On a scale of 1 to 5, how do you cope with academic pressure?
A. 1 (Poorly)
B. 2 (Fairly well)
C. 3 (Moderately well)
D. 4 (Well)
E.5 (Very well)

11. Have you ever sought academic counseling or support?
A. Yes
B.No

12. Have you ever engaged in self-harming behaviors?
A. Yes
B.No

13. If you answered "Yes" to the previous question, please briefly describe the reasons or triggers for self-harm. (Short Answer)
- Have you sought professional help or counseling for self-harm?
A.Yes
B.No

14. Do you experience other mental health issues not mentioned above? Please specify. (Short Answer)

15. On a scale of 1 to 5, how comfortable are you discussing your mental health issues with others?
A.1 (Very uncomfortable)
B. 2 (Uncomfortable)
C. (Neutral)
D. (Comfortable)
E.(Very comfortable)

16. Do you believe that technology (e.g., NLP and HCI) can positively impact mental wellness?
A.Yes
B.No
C.Unsure

17. Would you be open to using technology-based solutions to manage your mental health?
A. Yes
B. No
C. Maybe

18. Is there anything specific that your educational institution can do to better support students' mental health? Please provide suggestions. (Short Answer)

19. What challenges have you faced in accessing mental health resources at your institution? (Short Answer)

20. If you have used mental health resources on campus, please describe your experience. (Short Answer)

21. Are you comfortable discussing your mental health with friends or family?
A.Yes
B.No
C. Sometimes

22. Have you ever experienced stigma or discrimination related to your mental health issues?
A. Yes
B. No

23. What type of mental health support or services do you feel are lacking at your educational institution? (Short Answer)

24. Would you be interested in participating in workshops or programs related to stress management and mental wellness?
A. Yes
B. No
C. Maybe

25. How would you prefer to access mental health resources and information?
A. In-person workshops and counseling
B. Mobile apps or online platforms
C. Both
D. Other please specify:

26. Please rate the importance of the following factors in promoting mental wellness at your educational institution (1 = Not Important, 5 = Extremely Important):
A.1
B.2
C.3
D.4
E.5

27. Accessible counseling services
A.1 (Not Important)
B.2 (Somewhat Important)
C.3 (Neutral)
D.4 (Important)
E. 5 (Extremely Important)

28. Supportive academic environment

A. 1 (Not Important)
B.2 (Somewhat Important)
C.3 (Neutral)
D.4 (Important)
E.5 (Extremely Important)

29. Peer support groups

A.1 (Not Important)
B.2 (Somewhat Important)
C.3 (Neutral)
D.4 (Important)
E. 5 (Extremely Important)

30. Mental health awareness campaigns

A.1 (Not Important)
B.2 (Somewhat Important)
C.3 (Neutral)
D.4 (Important)
E. 5 (Extremely Important)

Chapter 10

Conclusion

Overall for our research, we undertook an extensive data-gathering effort, which was then followed by a thorough data preprocessing phase to ensure its suitability for model training. Upon further examination of the datasets and careful analysis of the results, it became apparent that the desired level of efficiency could not be fully achieved given the limitations of our current resources. In light of the necessity for a more comprehensive comprehension of the topic at hand, we have undertaken a significant measure by formulating a survey design that is specifically suited to align with our research aims. The chosen survey design exhibits potential for enhancing our dataset by incorporating significant insights since we have strategically intended to collect information that has been validated by mental health experts. The data obtained from this comprehensive survey process will form the basis for an improved model training phase in our final defence. The primary objective of our research is to enhance and optimize the performance of our model, thereby enabling us to provide comprehensive solutions for a wide range of mental health concerns. Ultimately, the integration of factual data with sophisticated modeling tools will provide hold the potential to unveil novel viewpoints and inventive strategies for tackling mental health issues.

Bibliography

[1] J. H. Friedman, "Greedy function approximation: A gradient boosting machine," *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.

[2] A. Liaw and M. Wiener, "Classification and regression by randomforest," *R News*, vol. 2, no. 3, pp. 18–22, 2002.

[3] G. Guo, H. Wang, D. Bell, Y. Bi, and K. Greer, "Knn model-based approach in classification," in *On The Move to Meaningful Internet Systems 2003: CoopIS, DOA, and ODBASE: OTM Confederated International Conferences, CoopIS, DOA, and ODBASE 2003, Catania, Sicily, Italy, November 3-7, 2003. Proceedings*, Springer, 2003, pp. 986–996.

[4] D. Coyle, G. Doherty, M. Matthews, and J. Sharry, "Computers in talk-based mental health interventions," *Interacting with computers*, vol. 19, no. 4, pp. 545–562, 2007.

[5] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The elements of statistical learning: data mining, inference, and prediction.* Springer, 2009, vol. 2.

[6] J. M. Burns, T. A. Davenport, L. A. Durkin, G. M. Luscombe, and I. B. Hickie, "The internet as a setting for mental health service utilisation by young people," *Medical Journal of Australia*, vol. 192, S22–S26, 2010.

[7] G. Doherty, D. Coyle, and M. Matthews, "Design and evaluation guidelines for mental health technologies," *Interacting with computers*, vol. 22, no. 4, pp. 243–252, 2010.

[8] M. Wrzesien, J.-M. Burkhardt, M. Alcañiz Raya, and C. Botella, "Mixing psychology and hci in evaluation of augmented reality mental health technology," in *CHI'11 Extended Abstracts on Human Factors in Computing Systems*, 2011, pp. 2119–2124.

[9] Y.-Y. Song and L. Ying, "Decision tree methods: Applications for classification and prediction," *Shanghai archives of psychiatry*, vol. 27, no. 2, p. 130, 2015.

[10] R. A. Calvo, K. Dinakar, R. Picard, and P. Maes, "Computing in mental health," in *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, 2016, pp. 3438–3445.

[11] D. Bone, C.-C. Lee, T. Chaspari, J. Gibson, and S. Narayanan, "Signal processing and machine learning for mental health research and clinical applications [perspectives]," *IEEE Signal Processing Magazine*, vol. 34, no. 5, pp. 196–195, 2017.

[12] R. G. Jackson, R. Patel, N. Jayatilleke, *et al.*, "Natural language processing to extract symptoms of severe mental illness from clinical text: The clinical record interactive search comprehensive data extraction (cris-code) project," *BMJ open*, vol. 7, no. 1, e012012, 2017.

[13] *Machine learning for mental health*, en, https://www.kaggle.com/code/kairosart/machine-learning-for-mental-health-1, Accessed: 2023-9-17, Jun. 2018.

[14] S. Chancellor, M. L. Birnbaum, E. D. Caine, V. M. Silenzio, and M. De Choudhury, "A taxonomy of ethical tensions in inferring mental health states from social media," in *Proceedings of the conference on fairness, accountability, and transparency*, 2019, pp. 79–88.

[15] K. Doherty, J. Marcano-Belisario, M. Cohn, *et al.*, "Engagement with mental health screening on mobile devices: Results from an antenatal feasibility study," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 2019, pp. 1–15.

[16] S. K. Mukhiya, F. Rabbi, K. I. Pun, and Y. Lamo, "An architectural design for self-reporting e-health systems," in *2019 IEEE/ACM 1st International Workshop on Software Engineering for Healthcare (SEH)*, IEEE, 2019, pp. 1–8.

[17] A. Ng, R. Kornfield, S. M. Schueller, A. K. Zalta, M. Brennan, and M. Reddy, "Provider perspectives on integrating sensor-captured patient-generated data in mental health care," *Proceedings of the ACM on human-computer interaction*, vol. 3, no. CSCW, pp. 1–25, 2019.

[18] S. R. Pendse, N. Karusala, D. Siddarth, *et al.*, "Mental health in the global south: Challenges and opportunities in hci for development," in *Proceedings of the 2nd ACM SIGCAS Conference on Computing and Sustainable Societies*, 2019, pp. 22–36.

[19] K. E. Ringland, J. Nicholas, R. Kornfield, E. G. Lattie, D. C. Mohr, and M. Reddy, "Understanding mental ill-health as psychosocial disability: Implications for assistive technology," in *Proceedings of the 21st International ACM SIGACCESS Conference on Computers and Accessibility*, 2019, pp. 156–170.

[20] P. Sanches, A. Janson, P. Karpashevich, *et al.*, "Hci and affective health: Taking stock of a decade of studies and charting future research directions," in *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 2019, pp. 1–17.

[21] A. Søgaard Neilsen and R. L. Wilson, "Combining e-mental health intervention development with human computer interaction (hci) design to enhance technology-facilitated recovery for people with depression and/or anxiety conditions: An integrative literature review," *International journal of mental health nursing*, vol. 28, no. 1, pp. 22–39, 2019.

[22] P. Chlebek, E. Shriberg, Y. Lu, T. Rutowski, A. Harati, and R. Oliveira, "Comparing speech recognition services for hci applications in behavioral health," in *Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers*, 2020, pp. 483–487.

[23] K. Daher, M. Fuchs, E. Mugellini, D. Lalanne, and O. Abou Khaled, "Reduce stress through empathic machine to improve hci," in *Human Interaction, Emerging Technologies and Future Applications II: Proceedings of the 2nd International Conference on Human Interaction and Emerging Technologies: Future Applications (IHIET–AI 2020), April 23-25, 2020, Lausanne, Switzerland*, Springer, 2020, pp. 232–237.

[24] S. K. Mukhiya, U. Ahmed, F. Rabbi, K. I. Pun, and Y. Lamo, "Adaptation of idpt system based on patient-authored text data using nlp," in *2020 IEEE 33rd international symposium on computer-based medical systems (CBMS)*, IEEE, 2020, pp. 226–232.

[25] O. Oyebode and R. Orji, "Deconstructing persuasive strategies in mental health apps based on user reviews using natural language processing.," in *BCSS@ PERSUASIVE*, 2020.

[26] C. Pretorius, D. McCashin, N. Kavanagh, and D. Coyle, "Searching for mental health: A mixed-methods study of young people's online help-seeking," in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–13.

[27] A. Thieme, D. Belgrave, and G. Doherty, "Machine learning in mental health: A systematic review of the hci literature to support the development of effective and implementable ml systems," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 27, no. 5, pp. 1–53, 2020.

[28] X. Wang, S. Hegde, C. Son, B. Keller, A. Smith, and F. Sasangohar, "Investigating mental health of us college students during the covid-19 pandemic: Cross-sectional survey study," *Journal of medical Internet research*, vol. 22, no. 9, e22817, 2020.

[29] M. Levis, C. L. Westgate, J. Gui, B. V. Watts, and B. Shiner, "Natural language processing of clinical mental health notes may add predictive value to existing suicide risk models," *Psychological medicine*, vol. 51, no. 8, pp. 1382–1391, 2021.

[30] S. R. Pendse, A. Sharma, A. Vashistha, M. De Choudhury, and N. Kumar, ""can i not be suicidal on a sunday?": Understanding technology-mediated pathways to mental health support," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–16.

[31] C. E. Smith, W. Lane, H. Miller Hillberg, D. Kluver, L. Terveen, and S. Yarosh, "Effective strategies for crowd-powered cognitive reappraisal systems: A field deployment of the flip* doubt web application for mental health," *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW2, pp. 1–37, 2021.

[32] N. Viani, R. Botelle, J. Kerwin, *et al.*, "A natural language processing approach for identifying temporal disease onset information from mental healthcare text," *Scientific Reports*, vol. 11, no. 1, p. 757, 2021.

[33] L. Balcombe and D. De Leo, "Human-computer interaction in digital mental health," in *Informatics*, MDPI, vol. 9, 2022, p. 14.

[34] T. Eagle, A. Mehrotra, A. Sharma, A. Zuniga, and S. Whittaker, “” money doesn’t buy you happiness”: Negative consequences of using the freemium model for mental health apps,” *Proceedings of the ACM on Human-Computer Interaction*, vol. 6, no. CSCW2, pp. 1–38, 2022.

[35] K. P. Kruzan, J. Meyerhoff, T. Nguyen, M. Reddy, D. C. Mohr, and R. Kornfield, ““i wanted to see how bad it was”: Online self-screening as a critical transition point among young adults with common mental health conditions,” in *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, 2022, pp. 1–16.

[36] A. R. Mahlous, B. Okkali, *et al.*, “A digital mental health intervention for children and parents using a user-centred design,” *Advances in Human-Computer Interaction*, vol. 2022, 2022.

[37] S. Singh, P. Yadwadkar, P. Suresh, *et al.*, “Therapy bot using machine learning for psychotherapy,” *International Journal of Research in Engineering, Science and Management*, vol. 5, no. 6, pp. 217–218, 2022.

[38] R. A. Tasnim and F. Z. Eishita, “Arcod: A serious gaming approach to measure cognitive distortions,” in *2022 IEEE 10th International Conference on Serious Games and Applications for Health (SeGAH)*, IEEE, 2022, pp. 1–8.

[39] T. Zhang, A. M. Schoene, S. Ji, and S. Ananiadou, “Natural language processing applied to mental illness detection: A narrative review,” *NPJ digital medicine*, vol. 5, no. 1, p. 46, 2022.

[40] *AIML and scientific charts*, en, https://www.kaggle.com/code/akilesh23/aiml-and-scientific-charts, Accessed: 2023-9-17, Jun. 2023.

[41] S. Akilesh, *Student-Mental-Health-Issues*, Jun. 2023.