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A Data-Driven Insight to Enhancing Stress Management Through Chatbot Interaction Among Undergraduate Students

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***Abstract*—Student stress management at the undergraduate level is a significant issue in the educational world. Therefore, this stress is a challenging issue that needs to be dealt with. As higher educational requirements stack up and their challenges grow, most students struggle to keep the required balance between their studies and preparation. This study establishes a deeper investigation of stress management among undergraduate students using machine-learning algorithms to identify factors contributing to stress and provide solutions. The research aims to illuminate the fundamental causes and health implications of stress for students. Through surveys and questionnaires, the study categorizes stress stages, identifying patterns and enabling the use of new stress management strategies. The findings are used to address concerns shared by undergraduate students and determine interventions to help them cope effectively which aim to provide students with the strength, knowledge, resources, and support needed to manage stress effectively and live a fulfilling life during their university years and future years. The findings will be used to develop policies and programs backed by science to ensure emotional and academic success for students.**

***Index Terms*—Stress Management, Undergraduate Students, Mental Health, Chatbot Interaction, Machine Learning Algorithms, Emotional Well-being, Human-Computer Interaction (HCI)**

I. Introduction

IN the modern age, Undergraduate students face numerous challenges in their academic journey, including academic pressure, financial strain, and social pressures [1], [2]. These pressures, driven by the competitive nature of the education system and societal expectations for achievement, can significantly impact their mental health and overall well-being [3]. Financial tension, tuition fees, living expenses, and education debt contribute to the complexities of student well-being, often leading to heightened stress and anxiety [4]. Additionally, students face social pressures to balance academic responsibilities with social activities and relationships, resulting in feelings of isolation and loneliness [5], [6]. Mental health issues like depression, anxiety, and stress are prevalent among students, emphasizing the need for accessible and destigmatized mental health resources on college campuses [4]. Maintaining a healthy work-life is crucial for undergraduate students to overcome these challenges [7].

Human-computer interaction is crucial in addressing the digital divide in mental health treatment, fostering interdisciplinary cooperation, and developing AI-driven solutions [8]. Innovative methodologies like virtual reality and immersive video games are being explored to enhance therapeutic results. Bangladesh is a leading participant in this movement, where technology is essential for complex health needs and mental health issues [9]. Integrating a social model framework with medical interventions can enhance personal agency and prioritize patients' needs within technical advancements [10].
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 [11].

Within this context, this study investigates stress management among undergraduate students in Bangladesh, examining the impact of academic pressure, social needs, and personal issues on mental health and academic performance. Through an interdisciplinary approach integrating psychology, technology, and machine learning, we aim to identify interventions to promote student resilience and mental well-being.

Based on that, our research addresses 3 research questions:
RQ1: How effective are HCI and ML algorithms in predicting stress levels among undergraduate students based on their interaction with a stress management chatbot?
RQ2: What is the efficacy of chatbot interactions in delivering immediate support and guidance for stress management among undergraduate students?
RQ3: How does the personalization of chatbot interactions, based on individual user data and preferences, find the effectiveness of stress management interventions?

We use machine learning algorithms to classify undergraduate students' stress levels into five stages, enabling the development of personalized interventions. The personalized chatbot, designed using HCI principles, uses survey questionnaires and qualitative data analysis to understand stress contexts and promote resilience.

A. *Research Contribution*

- Research suitable machine learning methods to achieve higher and more precise accuracy for classification.
- Utilize data-driven insights to develop personalized interventions that offer students real-time support, guidance, and resources.
- Explore the potential of chatbot technology as a scalable and accessible tool for addressing stress management challenges among undergraduate students.

II. Background Study

Stress management tools have garnered attention in mental health research, with Park et al. (2019) [12] and Potts et al. (2023) [13] emphasizing interactive questioning and personalized assistance. Both observed modest well-being improvements, especially among younger users. Meng et al. (2021) [14] highlighted the significance of emotional support in stress reduction, contrasting chatbot and human interactions. Abbas et al. (2022) [15] explored online chat platforms aiding mature students' transition to higher education, though students often preferred familiar messaging services. Klos et al. (2021) [16] demonstrated reduced anxiety symptoms in Argentinian college students using the AI chatbot Tess. Lin et al. (2021) [17] introduced Virtual Reality Group Chatbot Counseling (VRGC), integrating VR therapy with chatbot support. Gabrielli (2021) [18] and Patel et al. (2019) [19] employed chatbots for undergraduates, focusing on CBT, positive psychology, mindfulness, and emotion recognition to alleviate tension and anxiety. Fitzpatrick et al. (2017) [20] reported reduced depression symptoms through conversational self-help bots, while Hegde S. [21] underscored the prevalence of severe mental health challenges among U.S. college students. Chancellor S. [22] and Bone D. [23] explore machine learning and social media for early mental health detection. Pendse (2021) [24] critiques India's helpline system, suggesting tech-driven care. Daher K. [25] shows blue light's stress-reducing potential. Kornfield et al. [26] and Ng et al. [27] study online self-screeners and Fitbit's utility for mental health. Smith et al. [28] and Sen et al. [29] address student depression using web apps and machine learning in Bangladesh. Suresh (2022) [30] highlights NLP chatbots, while Pendse et al. (2019) [31] advocate mental health in HCI4D research.

III. Dataset

A. *Dataset Exploration and Analysis*

Existing public datasets proved insufficient for our goals, prompting the creation of a customized 30-question survey focused on mental health, academic stress, coping strategies, and technology-driven interventions. This tailored approach aims to address the unique challenges faced by Bangladeshi undergraduate students.

B. *Data Collection*

We collaborated with BRACU Counseling Unit psychiatrists to validate our survey and classify stress levels. The survey includes 30 questions on mental health and academic pressures, along with a 15-question assessment for stress and depression. Using snowball sampling via platforms like Discord and Facebook, we collected 473 confidential responses using Google Forms.

C. *Data Preprocessing*

A heatmap visualizes correlations between features and targets, with a threshold of 0.12 filtering significant factors. The dataset is split into training (80%) and testing (20%) subsets. Deployment integrates trained models into practical applications for real-time or batch processing.

D. *Survey Questions*

The survey questions used to construct the dataset are detailed in Table I.

IV. Methodology

Figure 1 illustrates our machine learning-based methodology for classifying depression patterns and providing suggestions. The workflow includes data collection, cleaning, normalization, and transformation to prepare data for training. The dataset is split into 80% training and 20% testing subsets. The model is trained on the training data and tested for depression level classification, with results analyzed to assess performance. Application development is carried out using the Flask framework, integrating the trained model, managing user data, and implementing features for result visualization and error handling.

TABLE I: Survey Questions

Section	Question	Response Format
Demographic	Please specify your gender identity.	Multiple choice
	Please select your age group.	Multiple choice
Inquiry about Potential Depression	Have you ever been diagnosed with depression?	Multiple choice
	On a scale of 1 to 5, how often do you experience symptoms of depression (e.g., sadness, loss of interest)?	Multiple choice
	Have you sought professional help or counseling for depression?	Binary choice
	Have you ever engaged in self-harming behaviors?	Binary choice
	Have you sought professional help or counseling for self-harm?	Binary choice
Inquiry about Potential Stress	How often do you feel stressed due to academic workload?	Multiple choice
	Do you engage in stress-relief activities (e.g., meditation, exercise)?	Binary choice
	On a scale of 1 to 5, how effective are your stress-management strategies?	Multiple choice
	Do you feel pressure to excel academically?	Binary choice
	On a scale of 1 to 5, how do you cope with academic pressure?	Multiple choice
	How frequently do you engage in activities or hobbies as a form of stress relief?	Multiple choice
	How much does a lack of proper sleep contribute to your overall stress levels?	Multiple choice
	What is your primary method of coping with academic or personal stress?	Multiple choice
Support and Services for Mental Well-being	Have you ever sought academic counseling or support?	Binary choice
	On a scale of 1 to 5, how comfortable are you discussing your mental health issues with others?	Multiple choice
	Do you believe that technology (e.g., NLP and HCI) can positively impact mental wellness?	Multiple choice
	Would you be open to using technology-based solutions to manage your mental health?	Multiple choice
	Are you comfortable discussing your mental health with friends or family?	Multiple choice
	Have you ever experienced stigma or discrimination related to your mental health issues?	Binary choice
	Would you be interested in participating in workshops or programs related to stress management and mental wellness?	Multiple choice
	How would you prefer to access mental health resources and information?	Multiple choice
	Please rate the importance of the following factors in promoting mental wellness at your educational institution (1 = Not Important, 5 = Extremely Important)	Multiple choice
	Accessible counseling services	Multiple choice
	Supportive academic environment	Multiple choice
	Peer support groups	Multiple choice
	Mental health awareness campaigns	Multiple choice
	Which stress-relief techniques or activities do you find most effective? (Select all that apply)	Checkboxes
	How effective do you find talking to someone (friend, family, counselor) about your stress and worries?	Multiple choice

A. Data Preprocessing

Data preprocessing begins with acquisition and analysis using Pandas for data manipulation and Seaborn for visualizations. Key attributes, including structure, column names, and summary statistics, are examined. Custom functions enrich the dataset by calculating value counts and generating random ages, with histograms visualizing age distributions to identify patterns and outliers. Outliers in the 'Random Age' column are handled using the interquartile range method. Categorical variables are converted into dummy variables, columns are renamed or dropped, and textual responses are mapped to numerical values for analysis. Aggregated response summaries provide insights into data distribution and trends.

B. Model Description

Various models are employed to understand stress dynamics among undergraduate students. Logistic regression identifies relationships between stressors and outcomes, while decision trees analyze decision-making processes. SVM defines stress thresholds, and ensemble methods like Random Forest and AdaBoost uncover complex patterns. Gradient Boosting explores stress's impact on well-being, and Naive Bayes estimates stress probabilities. This integration of models aids in a comprehensive understanding of student stress management.

V. Result Analysis

Table II evaluates the performance of machine learning models for stress management.

The Logistic Regression classifier performed well, accurately classifying 4 instances in class 1, 8 in class 2, 33 in class 3, 40 in class 4, and 4 in class 5. It achieved a precision score of 0.9814, recall of 0.9789, accuracy of 0.9789, and F1 score of 0.9788, demonstrating balanced performance.

The Decision Tree model achieved perfect classification, with no misclassifications across all classes: 4 instances in class 1, 14 in class 2, 33 in class 3, 40 in class 4, and 4 in class 5. It achieved perfect scores for precision, recall, accuracy, and F1 (all 1.0000). The Random Forest and Gradient Boosting models also classified all instances perfectly, achieving identical flawless scores.

The SVM model effectively classified stress levels, correctly identifying 4 instances in class 1, 9 in class 2, 33 in class 3, 40 in class 4, and 2 in class 5. However, it misclassified 2 instances in class 2 and 1 instance in class 5 as class 4, resulting in a precision of 0.8729, accuracy of 0.8421, and F1 score of 0.8045.

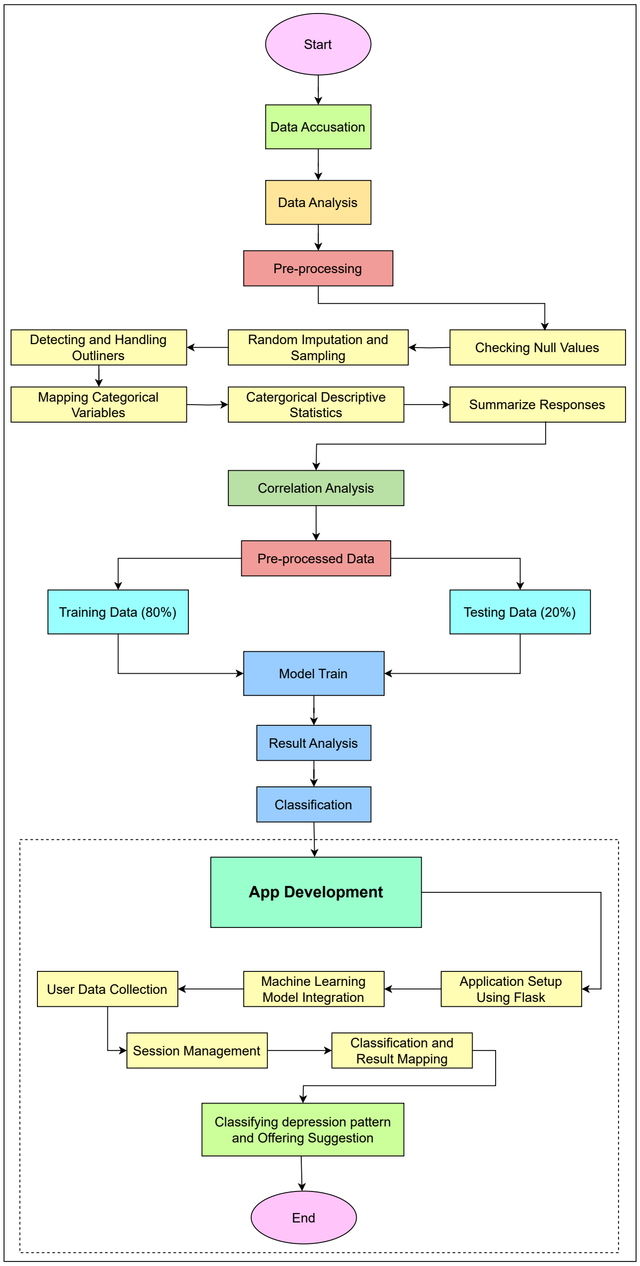

Fig. 1: Methodology Workflow

The AdaBoost model correctly classified 33 instances in class 3 and 34 in class 4 but failed to classify instances in classes 1, 2, and 5 accurately. It achieved a precision of 0.7492, accuracy of 0.8526, and an F1 score of 0.7918, demonstrating some robustness despite misclassification.

The Naive Bayes model correctly classified all instances in classes 1 and 5 but misclassified 2 instances in class 2, 2 in class 3, and 7 in class 4 as class 3. It achieved a precision of 0.9717, an accuracy of 0.9684, and an F1 score of 0.9689, making it a reliable choice.

Among all models, the Decision Tree stood out for its simplicity, interpretability, and perfect classification performance, accurately predicting all instances in the dataset. Its ability to handle both categorical and numerical data with minimal preprocessing makes it an ideal choice for classifying depression levels in this dataset.

TABLE II: Results of Different Models Architecture

Models	**Accuracy**	**F1-score**	**Precision**	**Statistics**		
				Classes	**T-P**	**T-N**
Logistic Regression	97.89%	97.88%	98.14%	Class 1	4	0
				Class 2	8	5
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
Decision Tree	100%	100%	100%	Class 1	4	0
				Class 2	14	0
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
SVM	84.21%	80.45%	87.2%	Class 1	4	0
				Class 2	9	5
				Class 3	33	0
				Class 4	40	0
				Class 5	2	2
Random Forest	100%	100%	100%	Class 1	4	0
				Class 2	12	2
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
AdaBoost	85.26%	79.18%	74.92%	Class 1	0	4
				Class 2	0	14
				Class 3	33	0
				Class 4	34	6
				Class 5	0	4
Gradient Boosting	100%	100%	100%	Class 1	4	0
				Class 2	14	0
				Class 3	33	0
				Class 4	40	0
				Class 5	4	0
Naive Bayes	96.84%	96.89%	97.17%	Class 1	4	0
				Class 2	3	11
				Class 3	24	9
				Class 4	33	7
				Class 5	4	0

A. *Comparative Analysis*

The summary of various studies on technological approaches to managing stress and anxiety among university students includes insights from different research endeavours. Sen et al. (2023) [29] utilized survey data from 750 students, achieving the best accuracy of 87% with Random Forest. Gabrielli et al. (2021) [18] evaluated the Atena chatbot with 1,496 students during COVID-19, reporting qualitative improvements. Fitzpatrick et al. (2021) [20] studied the Woebot chatbot with 101 college students, noting significant anxiety reduction. Patel et al. (2019) [19] utilized chat data from 150 students, finding the CNN model to be most accurate at 85%. Klos et al. (2021) [16] assessed the Tess chatbot with 150 students, observing reduced anxiety symptoms. Meng & Dai (2021) [14] compared emotional support from chatbots and humans with 300 users, determining that human support was more effective overall. Our Proposed Approach analyzed data from 473 students, achieving the highest accuracy of 100% and an average accuracy of 95%. These findings underscore the diverse techniques and their effectiveness in stress management among students.

VI. App Development

A. Chatbot Application Development

The web application uses a Flask framework in Python to predict depression severity and provide personalized treatment recommendations, utilizing a pre-trained decision tree model for user input analysis.

*1) **Application Setup and Security**:* The application development starts with the Flask framework, chosen for its simplicity and flexibility, ideal for rapid prototyping. A secret key ensures user data security and session integrity, making user sessions secure and tamper-proof.

*2) **Machine Learning Model Integration**:* A pre-trained decision tree model is the core predictive component of the application. Previously trained on a relevant dataset and saved in a joblib-compatible file, the model is loaded upon initialization to predict depression severity based on user inputs.

*3) **User Data Collection**:* User interaction with the application is facilitated through web forms containing a few questions spread across multiple pages, helping to collect data on various factors.

*4) **Classification and Result Mapping**:* User data is fed into a decision tree model to predict depression levels, ranging from mild to severe, including conditions like psychotic and treatment-resistant depression. The table III outlines five decision levels for depression, each with corresponding descriptions and tailored recommendations. The severity of symptoms ranges from no symptoms to extreme depression, with recommendations spanning lifestyle changes, psychotherapy, medication, and intensive treatments based on the severity. The web application harnesses the power of Flask, a lightweight and versatile Python framework, to create a user-friendly interface for predicting depression severity and providing personalized treatment recommendations.

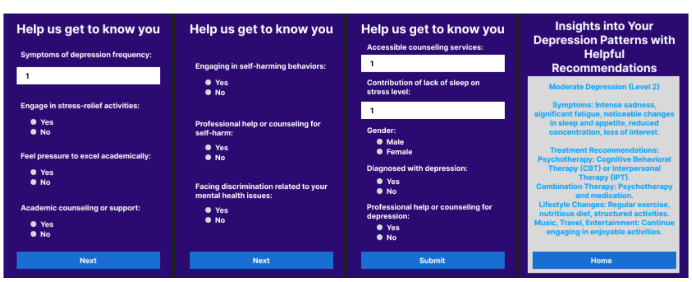

Fig. 2: Interface prototype sample of the app

TABLE III: Depression level mapping and recommendation

Decision Level	Description	Recommendations
Decision 1	No symptoms of depression. Feeling normal and mentally well.	1. Regular exercise and a balanced diet. 2. Joining support groups. 3. Emotional support from friends or loved ones. 4. Engaging in enjoyable activities like music. 5. Travel and entertainment.
Decision 2	Mild symptoms such as occasional sadness or low energy. Noticeable but not significantly impacting daily functioning.	1. Psychotherapy: CBT or IPT. 2. Combination Therapy: Psychotherapy and medication. 3. Lifestyle Changes: Regular exercise, nutritious diet, structured activities. 4. Continue engaging in enjoyable activities.
Decision 3	Moderate symptoms with frequent sadness, difficulty concentrating, and decreased motivation. Starting to interfere with daily activities.	1. Intensive Psychotherapy: Frequent CBT or other intensive therapy. 2. Higher doses or combinations of antidepressants. 3. Hospitalization for safety and intensive treatment. 4. Electroconvulsive therapy (ECT). 5. Strong support system and case management.
Decision 4	Moderate to severe symptoms including persistent sadness, hopelessness, and significant difficulty functioning daily.	1. Hospitalization for stabilization and safety. 2. Combination of antidepressants and antipsychotics. 3. ECT. 4. Intensive Psychotherapy: Post-psychosis treatment.
Decision 5	Extreme symptoms with high impairment or risk of self-harm or suicidal thoughts. Urgent intervention needed.	1. Advanced Medication Strategies: Combinations, mood stabilizers, ketamine infusions. 2. ECT. 3. Transcranial magnetic stimulation (TMS). 4. Vagus nerve stimulation (VNS). 5. Intensive Psychotherapy: CBT or DBT. 6. Regular exercise, healthy diet, sleep hygiene, integrative therapies. 7. Strong support network, frequent healthcare visits, support groups.

VII. Conclusion

In conclusion, Our study explores stress among undergraduate students using advanced machine-learning algorithms and human-computer interaction techniques. It identifies stress levels and patterns using survey data. A chatbot was integrated to assist students in stress management. The findings provide insights into potential interventions to support student mental health in academic settings, contributing to a deeper understanding of stress.

A. Future Work

We aim to enhance the practicality by integrating natural language processing (NLP), strengthening our chatbot system, and enabling more interactive user input and voice assistance. Hence, consulting a broader group of medical specialists will ensure scientifically proven interventions that meet the diverse needs of students.

References

[1] J. A. Ramley, "The changing role of higher education: Learning to deal with wicked problems," *Journal of Higher Education Outreach and Engagement*, vol. 18, no. 3, pp. 7–22, 2014.

[2] R. Gill and N. Donaghue, "Resilience, apps and reluctant individualism: Technologies of self in the neoliberal academy," in *Women's Studies International Forum*, vol. 54. Elsevier, 2016, pp. 91–99.

[3] N. S. Bekkouche, R. F. Schmid, and S. Carliner, "“simmering pressure”: How systemic stress impacts graduate student mental health," *Performance Improvement Quarterly*, vol. 34, no. 4, pp. 547–572, 2022.

[4] L. A. Scherer and A. I. Leshner, *Mental health, substance use, and wellbeing in higher education: Supporting the whole student*. National Academies Press, 2021.

[5] A. Kruisselbrink Flatt, "A suffering generation: Six factors contributing to the mental health crisis in north american higher education." *College Quarterly*, vol. 16, no. 1, p. n1, 2013.

[6] W. Leal Filho, T. Wall, L. Rayman-Bacchus, M. Mifsud, D. J. Pritchard, V. O. Lovren, C. Farinha, D. S. Petrovic, and A.-L. Balogun, "Impacts of covid-19 and social isolation on academic staff and students at universities: a cross-sectional study," *BMC public health*, vol. 21, no. 1, p. 1213, 2021.

[7] E. Martinez, C. Ordu, M. R. Della Sala, and A. McFarlane, "Striving to obtain a school-work-life balance: The full-time doctoral student," *International Journal of Doctoral Studies*, vol. 8, p. 39, 2013.

[8] H. Degen, S. Ntoa, and A. Moallem, *HCI International 2023–Late Breaking Papers: 25th International Conference on Human-Computer Interaction, HCII 2023, Copenhagen, Denmark, July 23–28, 2023, Proceedings, Part VI*. Springer Nature, 2023, vol. 14059.

[9] S. Raghavan, *(1971) A Global History of the Creation of Bangladesh*. Harvard University Press, 2013.

[10] S. Bucci, M. Schwannauer, and N. Berry, "The digital revolution and its impact on mental health care," *Psychology and Psychotherapy: Theory, Research and Practice*, vol. 92, no. 2, pp. 277–297, 2019.

[11] 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.

[12] S. Park, J. Choi, S. Lee, C. Oh, C. Kim, S. La, J. Lee, and B. Suh, "Designing a chatbot for a brief motivational interview on stress management: qualitative case study," *Journal of medical Internet research*, vol. 21, no. 4, p. e12231, 2019.

[13] C. Potts, F. Lindström, R. Bond, M. Mulvenna, F. Booth, E. Ennis, K. Parding, C. Kostenius, T. Broderick, K. Boyd, *et al.*, "A multilingual digital mental health and well-being chatbot (chatpal): pre-post multicenter intervention study," *Journal of Medical Internet Research*, vol. 25, p. e43051, 2023.

[14] J. Meng and Y. Dai, "Emotional support from ai chatbots: Should a supportive partner self-disclose or not?" *Journal of Computer-Mediated Communication*, vol. 26, no. 4, pp. 207–222, 2021.

[15] N. Abbas, J. Whitfield, E. Atwell, H. Bowman, T. Pickard, and A. Walker, "Online chat and chatbots to enhance mature student engagement in higher education," *International Journal of Lifelong Education*, vol. 41, no. 3, pp. 308–326, 2022.

[16] M. C. Klos, M. Escoredo, A. Joerin, V. N. Lemos, M. Rauws, and E. L. Bunge, "Artificial intelligence–based chatbot for anxiety and depression in university students: pilot randomized controlled trial," *JMIR formative research*, vol. 5, no. 8, p. e20678, 2021.

[17] A. P. Lin, C. V. Trappey, C.-C. Luan, A. J. Trappey, and K. L. Tu, "A test platform for managing school stress using a virtual reality group chatbot counseling system," *Applied Sciences*, vol. 11, no. 19, p. 9071, 2021.

[18] S. Gabrielli, S. Rizzi, G. Bassi, S. Carbone, R. Maimone, M. Marchesoni, and S. Forti, "Engagement and effectiveness of a healthy-coping intervention via chatbot for university students during the covid-19 pandemic: mixed methods proof-of-concept study," *JMIR mHealth and uHealth*, vol. 9, no. 5, p. e27965, 2021.

[19] F. Patel, R. Thakore, I. Nandwani, and S. K. Bharti, "Combating depression in students using an intelligent chatbot: a cognitive behavioral therapy," in *2019 IEEE 16th India Council International Conference (INDICON)*. IEEE, 2019, pp. 1–4.

[20] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): a randomized controlled trial," *JMIR mental health*, vol. 4, no. 2, p. e7785, 2017.

[21] 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, p. e22817, 2020.

[22] 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.

[23] 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.

[24] 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.

[25] 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.

[26] 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.

[27] 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.

[28] 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.

[29] S. K. Sen, M. S. A. Apurba, P. Mrittika, M. T. Anwar, A. Islam, and J. Noor, "Unveiling shadows: A data-driven insight on depression among bangladeshi university students," *Jannatun, Unveiling Shadows: A Data-Driven Insight on Depression Among Bangladeshi University Students*.

[30] 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.

[31] S. R. Pendse, N. Karusala, D. Siddarth, P. Gonsalves, S. Mehrotra, J. A. Naslund, M. Sood, N. Kumar, and A. Sharma, "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.