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DIAGNOSIS AND MONITORING OF MENTAL DISORDERS ASSISTED BY A MOBILE APPLICATION WITH IA IN THE CASE OF UNIVERSITY STUDENTS

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Abstract: Globally, it is estimated that approximately 254 million students are enrolled in universities (UNESCO, 2024). (UNESCO, 2024)of which 5.2 million are in Mexico (SEP, 2023). (SEP, 2023). Of these, 36.9% present some type of emotional disorder, such as stress, depression or anxiety, which are some of the main mental health problems among adolescents (INEGI, 2024). (INEGI, 2024).. At the Tecnológico Nacional de México/Instituto Tecnológico de Tuxtla Gutiérrez, in the Computer Systems Engineering program, 44% of students drop out of the program (Autores,2024). Previous studies in this institution indicate that these emotional disorders affect academic performance and contribute significantly to school dropout. (Ortiz, Basave, Sánchez, & Ortiz, 2021).. However, mental disorders are difficult to diagnose due to the similarity of their symptoms, which are often common among various mental illnesses. In this paper, we explore different metrics based on questionnaires and biological indicators, which serve as input data for machine learning methods. These methods allow identifying, diagnosing, monitoring and predicting the main mental disorders in university students, and their integration into technological tools such as mobile applications, chatbots, recognition and monitoring systems.
Keywords: Machine learning, internet of medical things, technological tools, wearable sensors, mental disorder scales.

INTRODUCTION

Currently, mobile devices are used for a wide variety of activities, including health management and monitoring in individuals, allowing healthcare professionals to intervene in a timely manner for the benefit of their patients (Li & Li, 2024; Barriga, 2024; Rakshitha, Mahadevi, & Durgadevi, 2023).. In addition, medical diagnostic systems whether semi-automated or fully automated, allow monitoring and obtaining valuable information remotely, delivered by patients through sensors, employing the technology of the Internet of Medical Things (Gupta, Sharma, & Kapoor, 2023; Gopichand, et al.). Some of the diagnostic systems incorporate artificial intelligence, machine learning techniques, unsupervised learning, supervised learning, neural networks, deep learning, reinforcement learning, ensemble models, time series based models, natural language processing, text mining and text analytics (Panicker & Gayathri, 2019; Vera, Gozme, & Guzman, 2024; Xia, et al.). These techniques are employed in different works with the aim of identifying symptoms of depression, stress, anxiety, alcohol abuse, dementia, drug abuse, psychosis, bulimia, anorexia, and bipolar disorder (Muetunda, et al, 2024; Di, Deroche, Trupkin, Chatterjee, & Pollo, 2024; Drousiotis, et al, 2023).. So, machine learning models take as input biological data (physical signs, physiological signals, and biomarkers) and from diagnostic instruments such as questionnaires (Talaat & El-Balka, 2023; Tao, Shaik, Higgins, Gururajan, & Zhou, 2021; Zakaria, et al, 2023).. In particular, the technological tools developed under these models and techniques contribute considerably to mental health wellness, aiding in the identification of mental disorders for timely diagnosis (Talaat & El-Balka, 2023; Varsha, Sri, & Anuvidhya, 2023; Mendoza, Tovar, & Contreras, 2024)..

In short, the greatest challenge facing educational institutions is to reduce school dropout, which is related to economic, social, family and mental health factors, among others. Therefore, universities must adopt strategies to improve terminal efficiency. In contribution, this article presents a general investigation on the different metrics, methods, devices and applications that allow diagnosing and evaluating the main mental disorders in university students.

PROBLEMS

In Mexico, according to INEGI, the school dropout rate at the higher level was 6.0% in the 2022/2023 school year, compared to the 8.1% recorded in the 2021/2022 school year. In an interview with the head of teaching at the TecNM/Instituto Tecnológico de Tuxtla Gutiérrez, he mentions that the terminal efficiency rate in the computer systems engineering career for the 2018 to 2022 cohort was 56.0% (Authors, 2024). This indicates that out of every 100 students who enter, 44 drop out. On the other hand, in Colombia, statistics on dropout and permanence in higher education, according to SPADIES, indicate an increase in the annual dropout rate at the university level, from 8.02% in 2020 to 8.89% in 2021 (SPADIES, 2023). A study conducted at the Universidad de la Costa, CUC, in Barranquilla in 2022 evaluated the academic status of students in a cohort spanning from 2014 to 2019, where the terminal efficiency rate of 74.53% at the university level, 65.9% at the technological level and 53.5% at the professional technical level (Caballero, 2022). This allows us to conclude that, in a technological university career, for every 100 students 44 drop out, as in Mexico.

In order to measure the problem, it is estimated that there are some 254 million students enrolled in universities worldwide (UNESCO, 2024). (UNESCO, 2024). In Mexico, national higher education enrollment will reach 5.2 million students by 2023 (SEP, 2023). (SEP, 2023).. In this context, a study conducted by INEGI on the perception of the emotional situation in the population of higher education students enrolled in the 2021-2022 school year, reveals that 36.9% feel tense or stressed, 26.5% feel desperate about academic work, 8.5% feel sad or depressed, and 2.2% have difficulties relating to other people their age. (INEGI, Press Release No. 709/22, 2022).. With regard to mental disorders in college students, depression, stress and anxiety are the main mental health problems in adolescents that can lead to very serious health situations, possibly caused by worries or mental tension, academic burden, social demands, fear of failure, lack of sleep and lack of time for recreational activities. (WHO, The Health of Adolescents and Young Adults, 2022)..

In turn, several studies suggest that mental disorders could negatively affect academic performance and increase the risk of dropping out of school (Singh, Kaur, Sharma, & Singh, 2024; Ortiz, Basave, Sánchez, & Ortiz, 2021; Agrawal, 2022).. On the other hand, students face a lot of pressure, especially in the academic part due to exams, assignments, projects, homework, family problems, work, and their relationship with their peers, this negatively influences their academic achievement (Ortiz, Basave, Sánchez, & Ortiz, 2021).. Similarly, anxiety is present in the majority of students who report having academic problems, for example, in Peru, during 2021, a significant prevalence of anxiety was reported, affecting 68% of students at three universities (Vera, Gozme, & Guzmán, 2024) and a study conducted in Chile shows that 92% of university students present some type of anxiety disorder (Micin & Bagladi, 2024). (Micin & Bagladi, 2011).. In addition, the late diagnosis of depression has led numerous students to abandon their studies, which generates dissatisfaction in life and, as a consequence, they represent a risk to society (Udoh, Usip, George, & Akpan, 2024).. Therefore, it is necessary to develop a mobile application that uses artificial intelligence and the internet of medical things to diagnose and monitor these mental disorders in college students.

MATERIAL AND METHODS

A systematic review is undertaken to identify the mental disorders presented by young students, the application of instruments based on questionnaires that measure the degree of suffering, and the biological indicators used by specialists for their evaluation in a clinical and objective manner.

This information is summarized and presented in Table 1. Where: the first column specifies the name of the disorder, the second column mentions the instruments based on questionnaires, and the third column presents the associated biological indicators. The following are some relevant references (Gomes, Pato, Lourenco, & Datia, 2023; Lee & Kim, 2022; Franco Paredes, Alvarez Rayón, & Ramírez Ruelas; Dunstan, Scott, & Todd, 2017; Hamilton, 1960).

In a clinical and objective manner, specialists can identify and diagnose mental disorders with the help of questionnaires and biological indicators (Armas, Talavera, Cárdenas, & de la Cruz, 2021) such as those presented in this article. These questionnaires consist of a set of questions that the patient must answer, and the response options are usually presented on a scale, generally Likert-type. As for biological indicators, they can be invasive, non-invasive sensors or biomarkers that allow the collection of physiological characteristics for the diagnosis of mental illnesses (Gomes, Pato, Lourenco, & Datia, 2023)..

As part of this work, a search was undertaken in the current market with the aim of identifying various portable devices that integrate sensors and that have high reliability, computational efficiency and continuous monitoring of physiological activity; in addition, they can recognize and collect biological data from the patient, transmitting the information autonomously to a centralized controller, either dynamically or through another system. Table 2 presents the most relevant portable devices along with the sensors they integrate.

On the other hand, also in this work, a review was carried out in the ACM, IEEE and Springer databases to identify applications, methods, models and algorithms that employ artificial intelligence, machine learning and deep learning for the treatment of mental disorders in university students. A search is undertaken with the words "mental disorder in students university" in recent years and for the discipline of computer science. In the ACM database, 1,715 results were obtained. In IEEE 185 results and in Springer 196. A title and abstract analysis was applied with the criterion of choice: software application oriented to mental disorders and with specific application to university students. Applying these filters, the results are 7 papers from ACM, 10 from IEEE and 9 from Springer.

Three mobile applications were identified:

1. ADHD-oriented and provides exercise routines. (Barrera, 2019).

2. Focused on stress management through conversations with the user. (Fernandez & Anu, 2022)..

3. Designed to identify stress, anxiety and depression through questionnaires. (Rakshitha, Mahadevi, & Durgadevi, 2023)..

In addition, seven systems were recognized:

1. Employs facial recognition and machine learning for stress detection (Ming, Anhum, & Keoy, 2023)..

2. Uses deep neural networks and the Mini-Xception algorithm to address stress. (Varsha, Sri, & Anuvidhya, 2023)..

3. Applies Gaita analysis and convolutional neural networks to recognize the risk of depression (Shao, et al., 2022).

4. Sleep monitoring system (Bojic, et al., 2023)..

5. IBM Monitoring System (Suo, 2024).

Mental disorder	Questionnaire-based instruments	Biological indicators
Depression.	HDRS, SRQ-20, DASS-21 and Zung Scale.	ECG, GSR and BVP.
Anxiety.	SRQ-20, DASS-21, Zung Scale and Beck Anxiety Scale.	HR, HRV, respiratory rate, diaphoresis, electromyography, and cortisol level.
Stress.	DASS-21, EPP, EEP-10, EEP-14, EEP-4 and CAE.	Temperature, respiration, pulse, skin blood volume, blood pressure and salivary cortisol.
Personality Disorder (PD).	MMPI, DMS-5, SCID-II and IPDE.	EEG.
Sleep Disorders (SD).	COS.	EEG and EOG.
Trauma.	HTQ.	ECG, GSR and BVP.
Eating Behavior Disorder (ED).	BULIT, EAT-40, BITE, QEWP-R, BES, BSQ, EDI, CIMEC and TFEQ.	ECG, heart rate monitors, BIA, DXA, accelerometer, gyroscope, BMI sensors.
Alcohol and drug abuse (AAD).	AUDIT and MULTICAGE-CAD4.	Elevated Gamma-Glutamyl Transferase (GGT) levels, elevated ST and ALT levels, mean corpuscular volume (MCV) and dilated or constricted pupils.
Adaptive disorder (AD).	Ca-MiR-R.	ECG, AED, EEG, GSR, HRV, electromyography and cortisol level.
Bipolarity.	M-3 Checklist, CGI-BP-M and HDRS.	Functional magnetic resonance imaging and study of the olfactory neuroepithelium.

Table 1 Instruments for the identification of mental disorders.

Handheld devices	Sensors
EQ02 LifeMonitor Belt by Equivital	Heart rate, respiratory rate, skin temperature, position, movement, electrocardiogram, respiratory monitor, thermometer and three-axis accelerometer (Equivital, 2024).
BioPatch HP from Zephyr Technology	ECG, accelerometer and respiratory monitor (Inc, 2024).
Hexoskin Smart Garment	Heart rate, respiratory activity, sleep, and respiratory rate. (Hexoskin, 2024).
Venu 3 Whitestone	GPS, GLONASS, Garmin Elevate heart rate monitor, barometric altimeter, compass, gyroscope, thermometer, accelerometer, pulse oximeter with acclimatization, and ambient light sensor. (Garmin, 2024).
Inspire 3 and Sense 2	Multipath heart rate optical, Electrical skin conductance, EDA scanner, SpO2, altimeter, three-axis accelerometer, skin temperature, ambient light, Wifi, NFC chip, GPS, vibration motor, speaker and mic. (Fitbit, 2024).
Empatica EmbracePlus and EmpaticaCARE	Ventral EDA for electrodermal activity, an advanced optical PPG sensor for measuring PR and PRV, a digital skin temperature sensor, an accelerometer, and a gyroscope. (Empatica, 2024).
Xiaomi Smart Band 9	Accelerometer, gyroscope, optical heart rate sensor and ambient light sensor (MI, 2024).
Fitbit Inspire 3 and Apple Watch	Functionalities for stress monitoring and sleep profile analysis. (Apple, 2024; Fitbit, 2024).

Table 2. Handheld devices and the sensors they integrate.

6. Uses K-Means, AGENES and DKM for the detection of depressive symptoms. (Mendoza, Tovar, & Contreras, 2024)..

7. Algorithm based on decision trees and Markov Chain Monte Carlo to predict suicidal ideation (Drousiotis, et al., 2023)..

Five models were identified:

1. Classification model for anxiety using machine learning techniques. (Vera, Gozme, & Guzman, 2024)..

2. Neuro-fuzzy adaptive model for the detection of depression using questionnaires. (Udoh, Usip, George, & Akpan, 2024)..

3. Prediction model for depression using a neural network (ANN) and backpropagation techniques with the sigmoid function. (Quintero López, Gil Vera, & Mazo Zea, 2023)..

4. Employing discriminant analysis for the prediction of depression. (Di, Deroche, Trupkin, Chatterjee, & Pollo, 2024).

5. Applies a neural network with multimodal graphs for depression detection (Xia, et al., 2024).

Five tools were also identified:

1. Targeting sleep disorders, monitors activity on Wi-Fi network (Zakaria, et al., 2023).

2. Uses convolutional neural networks to identify emotions (Welaratne & Ratnayake, 2022)..

3. Applies questionnaires to measure stress levels. (Zaiyadi, Muhaiyuddin, Mutalib, Rambli, & Shafia, 2024)..

4. Employs machine learning models to identify anxiety (Zhang, Zhao, & Yang, 2024)..

5. It is a program that offers physical exercise and detects anxiety. (Brown, et al., 2024).

Also found:

1. Two mental health-focused chatbots that integrate conversations, neural networks, deep learning, and transfer learning (Nayar, Attar, Kachwala, & Wagh, 2022; Ogamba, Gitonga, Muriithi, Olukuru, & Sevilla, 2023)..

2. Robotic trainer designed to help manage anxiety through relaxation exercises. (Rasouli, et al., 2023)..

3. Virtual human promoting mental wellness through conversations. (Feijóo, et al., 2023)..

4. Virtual assistant that detects anxiety through conversational interaction and questionnaires. (Antunes, et al., 2023)..

5. Anxiety-oriented conversation-based game (Cai, Li, Chen, Wang, & Jia., 2023).

It is important to mention that no papers were found for personality disorders, trauma, eating behavior disorder, alcohol and drug abuse, adaptive disorder, schizophrenia or bipolarity oriented to university students.

Figure 1 shows the frequency of contributions by mental disorder, the disorder where most work has been done is depression, with 7 contributions, followed by anxiety with 6 contributions, stress with 5 contributions, mental health and emotional wellbeing with 5 contributions, sleep disorder with 2 contributions and one oriented to attention deficit and hyperactivity disorder.

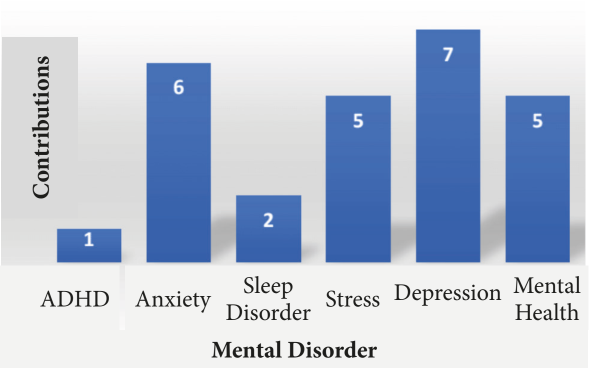

Figure 1. Frequency of contributions by mental disorder (Authors, 2024).

DISCUSSION

Based on the analysis, the disorders that most concern researchers based on the number of contributions made in the years 2023 and 2024 are depression, followed by anxiety, stress, mental health, sleep disorder and attention deficit hyperactivity disorder. These technology contributions apply or develop artificial intelligence methods, questionnaire-based data collection, natural language or voice recognition, multimodal graphics and databases.

CONCLUSIONS

The impact of mental disorders on dropout and failure rates is very serious, as they manifest themselves with symptoms such as sadness, feelings of emptiness, anger, anxiety and sleep disturbances, as well as a general loss of initiative and interest in activities. Anxiety, depression, stress and sleep disorders are the most common disorders in higher education, which makes it essential to integrate emerging technologies that obtain information from biological indicators and questionnaire-based instruments to support the timely diagnosis of these disorders in university students and contribute to the reduction of dropout rates. It is also proposed the development of applications based on the Internet of Medical Things to monitor and identify mental disorders in students through data obtained from non-invasive sensors, which will allow correcting situations in the classroom that trigger alterations in related variables and, thus, reduce the dropout rate.

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