AN AI-POWERED SELF-ACCESS AND SELF-MONITORING APPLICATION FOR DEPRESSION AND ANXIETY

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ABSTRACT

Mental health, particularly anxiety disorders, has been recognized as a significant global challenge, profoundly impacting the quality of life for individuals worldwide. Traditional barriers, such as geographical constraints and the inflexibility of mental health care, have hindered efforts to address these issues effectively. Therefore, in this study, an advanced mental health monitoring system incorporating artificial intelligence (AI) technology has been proposed to overcome these limitations. Specifically, this system integrates smart wristbands to collect sleep data from patients. The collected data is then visualized on both web and mobile platforms in real-time, enabling therapists to monitor progress and design appropriate treatment plans. Additionally, AI technology is utilized to analyze historical data, providing personalized recommendations for sleep schedules and predicting sleep quality for the upcoming week. This system offers tailored interventions for individual patients. It empowers them to actively participate in their mental health treatment actively, improving their overall well-being and fostering a healthier mindset.

ỨNG DỤNG TỰ GIÁM SÁT VÀ TỰ TRUY CẬP DỰA TRÊN CÔNG NGHỆ AI: GIẢI PHÁP HỖ TRỢ ĐIỀU TRỊ TRẦM CẢM VÀ LO ÂU

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TỪ KHÓA

Sức khỏe tâm thần
Rối loạn lo âu
Trí tuệ nhân tạo (AI)
Giám sát sức khỏe tâm lý
Thiết bị đeo tay thông minh

TÓM TẮT

Sức khoẻ tâm thần, cụ thể là các tình trạng rối loạn lo âu, là một thách thức lớn trên toàn cầu, ảnh hưởng đến chất lượng cuộc sống của con người. Các khó khăn như khoảng cách và thiếu linh hoạt trong chăm sóc sức khỏe tâm thần đã cản trở việc giải quyết các vấn đề. Chính vì vậy, nghiên cứu này đề xuất một hệ thống giám sát sức khoẻ tâm lý tiên tiến kết hợp với công nghệ trí tuệ nhân tạo (AI). Cụ thể hơn, hệ thống này tích hợp thiết bị đeo tay thông minh để đo dữ liệu về giấc ngủ của người bệnh. Sau đó hệ thống sẽ trực quan hóa dữ liệu lên hai nền tảng web và di động theo thời gian thực để các nhà trị liệu có thể quan sát và đưa ra các liệu trình phù hợp. Song song đó, công nghệ AI cũng sẽ được áp dụng để dựa vào các dữ liệu quá khứ, đề xuất cho người bệnh thời gian đi ngủ và dự đoán chất lượng giấc ngủ của một tuần kế tiếp. Hệ thống này không chỉ cung cấp các điều trị cá nhân cho từng bệnh nhân, mà còn khuyến khích bệnh nhân tích cực tham gia điều trị sức khỏe tâm thần của mình, từ đó cải thiện chất lượng cuộc sống và có một tinh thần khoẻ mạnh.

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1. Introduction

In modern society, health has become increasingly important as it reflects both the potential for growth and the quality of life within a community. Beyond physical health, mental health has emerged as a pressing issue, particularly in today's context of heightened stressors. Factors such as work-related pressures, family responsibilities, and many external pressures like social media interactions have compounded mental well-being challenges. The World Health Organization (WHO) reports that more than 970 million people worldwide are affected by mental health disorders, with anxiety and depression being the most common [1], as shown in Figure 1. This is completely reasonable because social changes, especially factors such as urbanization, social isolation, or economic crisis, have contributed to the severity of the problem.

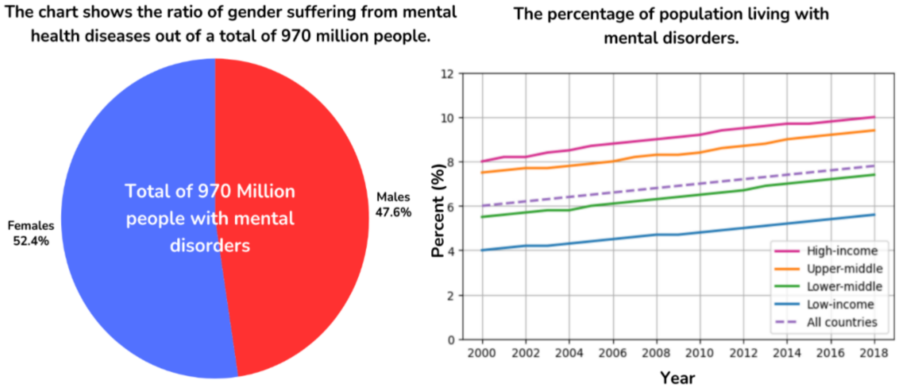

Figure 1. *The statistics provided by WHO* [1]

In addition, a UNICEF report [2] highlights that 1 in 7 individuals aged 10 to 19 face mental health issues, with anxiety and depression being the most prevalent disorders among this age group. This is because nowadays, young people face enormous pressure to maintain academic excellence and secure a stable career in a highly competitive environment.

It is evident that in many nations, particularly developing countries, mental health issues are often overlooked by governments, as they are still frequently dismissed as insignificant or merely a natural part of life [3]. As a result, countries around the world face many barriers to provide effective and equitable access to mental health care. The major challenges facing us today include:

- Lack of mental health care resources: One of the biggest challenges is the lack of resources, including personnel and facilities. A report from Okechukwu [4]indicates that in many low-income countries, the number of psychiatrists is less than 1 per 100,000 people. This results in mental health care being largely dependent on families or communities without professional support.
- Inequality and stigma: Research [5] indicates that individuals with mental illnesses in developing countries face social stigma or are even ostracized by their families and communities.
- Limitations of traditional healthcare approaches: Most methods focus on individual therapies, such as medication, without fully addressing the social and environmental factors related to the patient [6].

Based on those reasons and pieces of evidence, this study proposes a novel approach to leveraging AI techniques in dealing with mental health care issues. Our proposed system consists of a third-party hardware device, a web-based, and a mobile application to solve mental health problems. The hardware device is used for each patient to collect data like sleeping scores, etc. Lastly, the collected data undergoes preprocessing and real-time visualization on both the web and mobile applications. This study provides evidence of the system's feasibility and compares its effectiveness with other proposed solutions.

The mindLAMP platform is designed to collect sensor metadata from wearable devices and patient surveys without disrupting the patient's routine. Healthcare professionals and researchers can customize and schedule therapeutic activities, analyze data in real-time, and make informed decisions regarding treatment and care [7]. While mindLAMP is a powerful tool, several limitations hinder its effectiveness. Setting up and managing dedicated servers for mindLAMP requires significant technical expertise and financial investment, which can be particularly challenging for smaller healthcare facilities. Additionally, despite the use of strong encryption protocols, ensuring full compliance with data privacy standards - such as HIPAA and GDPR - remains a concern, especially when transmitting sensitive health data.

Especially, some studies proved that health is significantly influenced by the quality of one's sleep by SleepSense [8] - [10]. In many cases, the current home sleep monitoring devices are either inconvenient to use or do not provide adequate sleep information. SleepSense, a cost-effective and non-contact sleep monitoring system, is proposed to continuously identify sleep states, such as in-bed movement, out-of-bed movement, and respiration rate, in order to surmount these challenges. However, the methods of [8] - [10] are less effective in detecting subtle in-bed movements like hand tremors or leg jerks, as they may be too slight for Doppler radar to capture. System performance may also be affected by the subject's distance from the radar and their sleeping position.

On the one hand, the studies [11] and [12] propose IoT-based architectures for sleep quality monitoring that integrate WELM and PSO for sleep stage classification. While these models enhance accuracy in evaluating a patient's mental and sleep state, they share a common limitation - high memory consumption, which negatively affects system responsiveness and overall monitoring efficiency.

2. Methodology

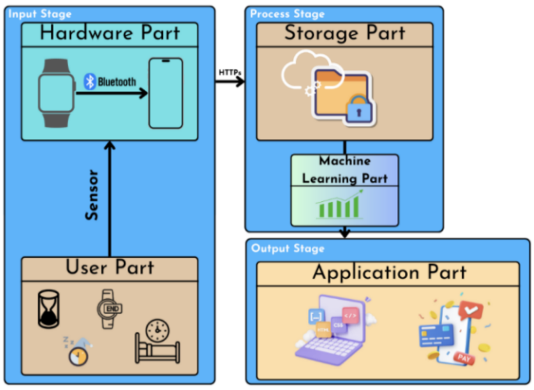

Figure 2. *General system design diagram*

As shown in Figure 2, the recommended system includes three stages: input, process, and output. In the input stage, the smartwatch collects data, including user sleeping time, wake-up time, and sleeping quality. Then, data are stored in a cloud system for preprocessing and analyzing. Simultaneously, data are tracked and applied to a suitable machine-learning model. Lastly, the data are visualized on both web and mobile applications for continuous real-time observation by patients and physicians. The division into phases ensures clarity in defining responsibilities and relationships between different modules while adhering to design principles such as modularity, scalability, and maintainability.

2.1. Analyzing collected data

To enhance data variety, patients' data collected through smart wearable devices are combined with the Kaggle dataset illustrated in Figure 3. Therefore, the Kaggle dataset is preprocessed to normalize and de-noise before being analyzed and used to train machine-learning models.

	Start	End	Sleep quality	Time in bed	Wake up	Sleep Notes	Heart rate	Activity (steps)
0	2014-12-29 22:57:49	2014-12-30 07:30:13	100%	8:32	:)	NaN	59.0	0
1	2014-12-30 21:17:50	2014-12-30 21:33:54	3%	0:16	:|	Stressful day	72.0	0
2	2014-12-30 22:42:49	2014-12-31 07:13:31	98%	8:30	:|	NaN	57.0	0
3	2014-12-31 22:31:01	2015-01-01 06:03:01	65%	7:32	NaN	NaN	NaN	0
4	2015-01-01 22:12:10	2015-01-02 04:56:35	72%	6:44	:)	Drank coffee:Drank tea	68.0	0
...	...	...	...	...	...	...	...	...
882	2018-02-12 21:54:14	2018-02-13 07:02:15	91%	9:08	NaN	NaN	NaN	56
883	2018-02-13 23:49:19	2018-02-14 07:00:53	81%	7:11	NaN	NaN	NaN	64
884	2018-02-14 21:24:05	2018-02-15 06:20:52	71%	8:56	NaN	NaN	NaN	3316
885	2018-02-15 21:36:32	2018-02-16 06:50:31	80%	9:13	NaN	NaN	NaN	6555
886	2018-02-16 22:52:29	2018-02-17 07:48:04	91%	8:55	NaN	NaN	NaN	2291

Figure 3. *The sleeping dataset on Kaggle [13]*

2.2. Identifying and handling data gaps

To be more specific, the dataset demonstrates common issues, including missing and sporadic values. Any data that occurs between these intervals is not recorded and disregarded. Furthermore, the threshold normalization procedure is implemented on all components of the data set to optimize data cleaning. This approach assists the model in preventing the learning of data that is of inferior quality, which could potentially have a detrimental effect. Furthermore, the method of identifying anomalous data is widely acknowledged as an effective method for improving the accuracy of data sets that are employed in algorithms and models.

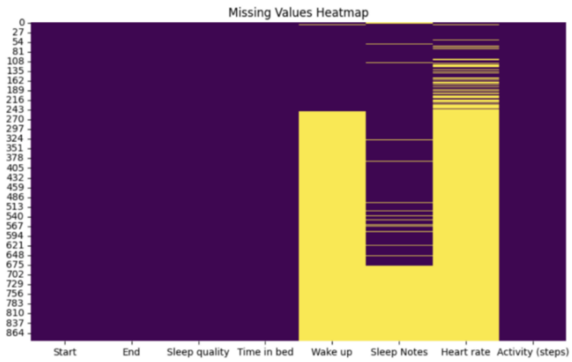

Figure 4. *The visualization of missing data in the provided dataset*

As shown in Figure 4, three fields including "Wake up", "Sleep Notes", "Heart rate" are missing some values. Fortunately, those fields are not used to forecast the next value. Instead of filling its, those fields are removed to make a clean dataset. Additionally, strategies and methodologies are implemented to standardize and purify the collected data, which is subsequently analyzed and compiled to produce the necessary statistics. It is imperative to recognize patterns in the data, as it is continuous. Consequently, it is imperative that we assess it in order to understand the temporal variations. Further, it is essential to evaluate this dataset for any fluctuations in the levels of these factors relative to one another and potential correlations or disparities, as a result of the inherent character of these components within the environment.

To address these challenges and ensure data continuity, data visualization plays a critical role. Visualization helps identify gaps, patterns, and irregularities in the collected sleep data, allowing analysts to pinpoint where and when data loss occurred. Once these gaps are detected, they are addressed using advanced data interpolation techniques, which estimate missing values based on existing data points and observed trends.

2.3. Techniques for data interpolation

One of the widely adopted techniques for handling missing sleep data involves using the interpolation methods from Python's Pandas library. These methods generate approximate values for missing entries based on nearby data points, ensuring that reconstructed data aligns with existing patterns as shown in Figure 5a. Furthermore, a correlation matrix enables the comprehensive examination of correlations between variables. It assists in the identification of closely associated variables, promotes predictions, or improves the understanding of the analyzed data. A matrix is a tabular representation in which each column contains a correlation coefficient. If the correlation value is "1" the variables are strongly associated, "0" indicates a neutral relationship, and "-1" indicates a feeble relationship. The correlation matrix, as previously illustrated, offers a comprehensive understanding of the relationships between the elements in the dataset. Figure 5b shows that the "Sleep starting time," "Sleep ending time," "Sleep quality," and "Time in bed" have a correlation between each field. Therefore, four fields are used as input data for the ML models.

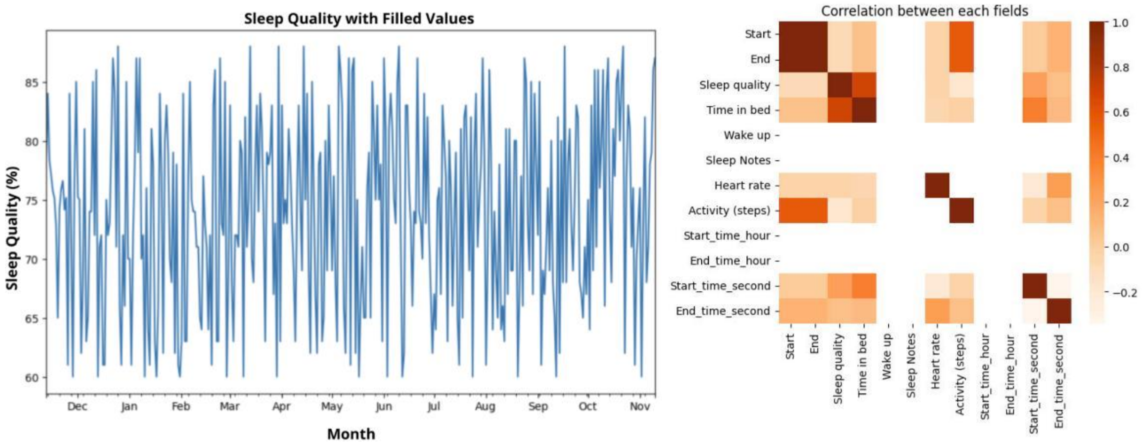

Figure 5. *a) The chart represents the reconstructed data, b) the correlation between data fields*

3. Implementation results and discussion

3.1. System Implementation

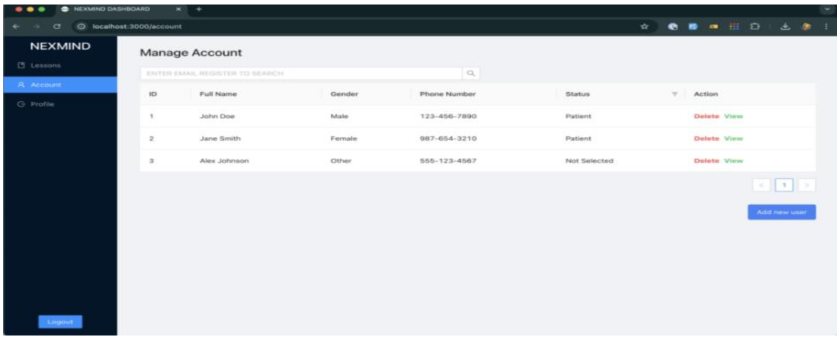

Figure 6. *The account page to manage patients for each doctor*

The web application interface is built using the ReactJS library and integrates OAuth 2.0 plug-ins [14] to manage patients and secure their data in compliance with HIPAA [15] and GDPR [16] standards. Specifically, the patient data monitoring table for doctors incorporates security technologies, as shown in Figure 6, ensuring privacy and data integrity.

This application allows patients to have a friendly interface for going through therapeutic exercises, recording health metrics, and providing feedback. The patients could monitor their health metrics collected from the Huawei Watch GT 3: heart rate, sleep quality, and physical activity summaries. The patient would be able to attend therapeutic lessons given to him or her by any healthcare professional in order not to exclude an active patient position in health process.

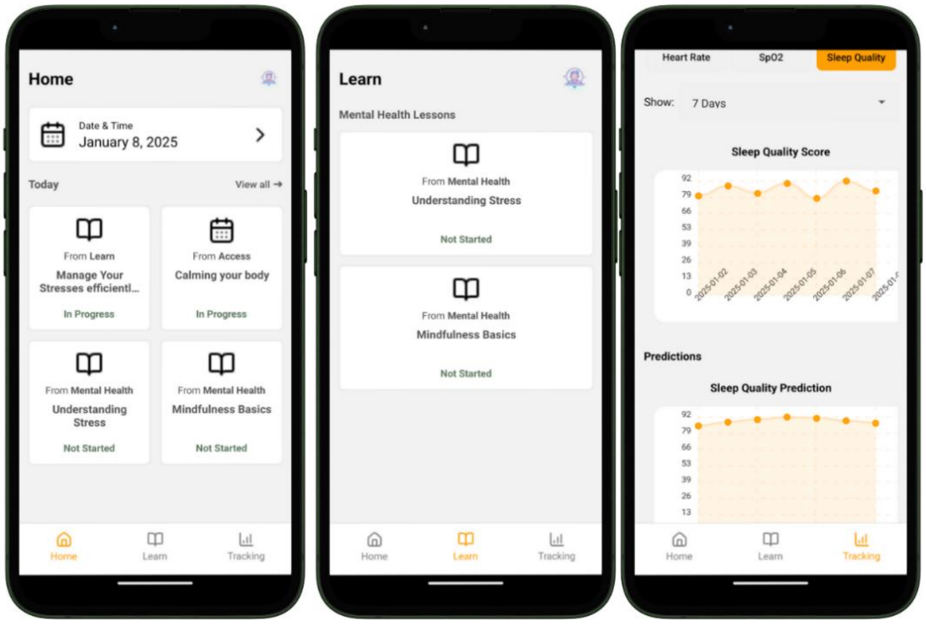

Figure 7. (a) *The homepage screen, (b) The learn screen, (c) The tracking and predicting sleep quality score*

Figure 7a shows the homepage screen with many learning modules for patients to control their depression. The learn screen in the mobile application is a dedicated space where patients can view and manage their mental health lessons, as shown in Figure 7b. It shows a list of available lessons. Additionally, the screen allows patients to review past lessons they have completed and explore upcoming lessons assigned by their healthcare providers. Furthermore, Figure 7c shows the Sleep Quality Scores section, which depicts the line graph representing trends in sleep quality. Besides, the prediction part describes an intended feature where an AI algorithm would predict future trends from historical data using the LSTM Model.

3.2. Training

The experiments are conducted on a dataset containing 887 samples (80% train, 20% validation) with 8 sleep-related attributes. Four features were extracted for analysis: Start_time_second, End_time_second, Time in bed, and Sleep quality. LSTM was trained for 100 epochs with early stopping. We applied a learning rate scheduler, early stopping, and saved the best model checkpoints during training. Besides, we used simple Grid Search to test combinations of key parameters. Training was performed on a system with RTX 4060 Laptop GPU, 16GB RAM, and Intel i7-12700H CPU.

3.3. Evaluation

Table 1 contrasts the performance of a variety of machine learning models in predicting Sleeping Start Time and Sleep Quality using three evaluation metrics: Execution Time, Accuracy, and R2-Score. Long-Short Term Memory (LSTM) exhibits the most accurate predictive performance among the models, with an R2-Score of 0.87 and an Accuracy of 78.35% for Sleeping Start Time and an R2-Score of 0.81 and an Accuracy of 83.10% for Sleep Quality. Nevertheless, the execution duration of 180 seconds is the longest (LSTM), suggesting a compromise between computational efficiency and accuracy. The fastest model is Linear Regression (LR), with an execution time of just 2 seconds. However, its performance degrades significantly. Higher execution efficiency and accuracy are observed with XGB, followed by GB.

Table 1. *Comparison and evaluation of criteria among machine learning models*

Prediction Results	Sleep Onset Time		Sleep Quality		Execution Time
Evaluation Metrics	**R2-score**	**Accuracy (%)**	**R2-score**	**Accuracy (%)**	**(seconds)**
Linear Regression (LR)	0.14	69.527	0.61	76.877	2
Gradient Boosting (GB)	0.10	69.259	0.57	76.202	55
Extreme Gradient Boosting (XGB)	0.73	70.611	0.60	76.452	90
Long-short Term Memory (LSTM)	0.85	78.346	0.81	82.069	180

Overall, our application aims to inherit the strengths and improve the limitations of other recommendation systems by developing a user-friendly platform for both doctors and patients, including a web and mobile application. The interface is designed to allow doctors to easily monitor patient metrics, assign lessons, and track progress, while patients can seamlessly follow lessons, review health metrics, and receive timely notifications, as shown in Table 2, especially when compared to existing applications [7], [8], [11]. Furthermore, the following strengths have been achieved after testing and validation of the application:

- Successfully developing a real-time patient data recommendation app.
- Optimizing the application for both web and mobile platforms.
- Providing features with accurate, detailed information that is easily accessible.

Table 2. *Comparison and evaluation of criteria between the proposed system and other systems*

Aspect	Our	mindLAMP [7]	Feng Lin [8]	Nico Surantha [11]
Open-source	×			
Easy Accessibility	×	×		
Low Development Cost	×		×	
Web/Mobile Application	×	×		
Multiple Smart Devices Support	×			
Reliability and Stability	×	×	×	×

3.4. Discussion

Our study shows that this AI-powered app is a practical and promising tool for anyone managing depression or anxiety. It takes real-time sleep data from a wearable device and uses smart predictions to offer personalized advice, all on an easy-to-use platform for both patients and their doctors. Our AI was impressively accurate in forecasting sleep quality, which proves we can turn raw data into genuinely helpful guidance. Unlike other systems that can be complex or costly, our app is designed to be more accessible and user-friendly. Ultimately, this work helps fill a critical gap, creating a tool that empowers people to be active partners in their own mental health journey.

4. Conclusion and future improvements

The project carries several important ramifications for how technology is applied to mental health, bridging a gap between data analysis and actionable outcomes. The system will be developed with a user-friendly platform for both doctors and patients in terms of Web Dashboard and Mobile Application. The interface is designed to allow doctors to easily monitor patient metrics, assign lessons, and track progress, while patients can seamlessly follow lessons, review health indicators, and receive timely notifications. However, to maintain the accuracy and reliability of predictive models, continuous validation with real-world data is essential.

To ensure consistent performance over time, algorithms should be fine-tuned for varying data and evolving user behavior. Key recommendations include enhancing platform interactivity and personalization through adaptive notifications, customizable lessons, and real-time feedback. The integration of LSTM-based models contributes by forecasting sleep metrics like duration and overall trends. Ongoing validation with real-world health data and continuous model updates are essential to maintain accuracy across diverse patient populations.

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