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Sensor Technology in Early Warning System for College Students' Mental Health Risk

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The increasing prevalence of mental health issues among college students necessitates innovative approaches to address them. This study was carried out to integrate sensor technology into a system to identify at-risk students and warn them and their caregivers. Privacy concerns, lack of technical expertise, and financial constraints that hinder the effective implementation of the system were addressed by introducing data protection protocols, development by experts, and funding for technology development. The feasibility of the system was validated in a case study in which the results demonstrated the successful operation of sensor technology in monitoring students' emotional status. The system also helped students engage and promote personalized learning. The results of this study proved the transformative potential of sensor technology in education.

1. Introduction

The majority (74%) of college students suffer moderate to severe psychological distress, including anxiety disorder (36%) and depression (28%).(1) Such mental distress considerably affects the learning and life of the students. Suicide that might be caused by such mental distress has become the second leading cause of death of college students, with about 1,100 students committing suicide in China each year.(2) This has raised social concern and necessitated early and accessible support systems. However, off-campus counseling agencies are under considerable pressure as they struggle to meet the rising demand for mental health counseling, leading to increased awareness. In addition, the pandemic caused by coronavirus disease pandemic exacerbated students' mental health problems and highlighted the inadequacy of current services. Even though the proportion of students experiencing severe mental distress decreased from 23% in 2022 to 19% in 2024,(3) the number of students who experience loneliness and stress from academic, financial, and social aspects is increasing.(4)

Although mental distress or illnesses are often concealed by patients and their families, an increasing number of students are seeking help to recover from these conditions.(4) While

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universities and schools are struggling to help students and find solutions to these problems, technologies have been used to provide mental-health-related services on campus. Sensor technology offers a promising solution for developing an early warning system for the psychological crises of students. By using wearable devices and mobile applications, students' physiological and emotional status can be monitored, and collected data can be used to improve the performance of those devices through the improvement of the algorithm. The algorithm learns from the collected data, predicts the patterns indicative of mental distress, and alerts authorities to take necessary measures. Stress and anxiety are assessed on the basis of the data of heart rate variability (HRV) and sleeping parameters collected by wearable devices, and mood and stress are monitored by mobile applications, thereby enabling an early warning of students' psychological status.

Sensor technology plays an important role in collecting such data and is applied in various systems and devices (Fig. 1).[5] Continuous data collection and analysis enable the early identification of at-risk students, allowing authorities such as college administrators to provide effective support. Therefore, in this study, we aim to integrate sensor technology into an early warning system for students' mental health. The system was evaluated by a literature review and tests, the results of which validated the system's benefits and challenges to be addressed.

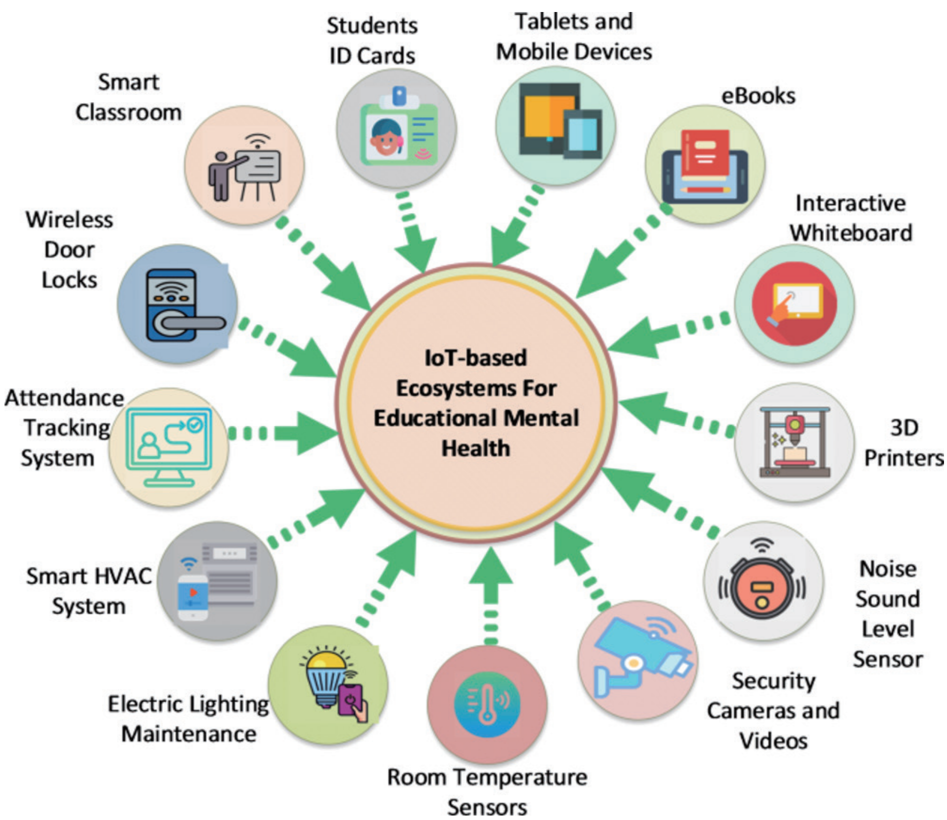

Fig. 1. (Color online) Mental health monitoring system and its components.

2. Limited Support of Colleges

College students are actively seeking ways to secure their psychological well-being. More than 60% of college students experienced more than one mental health disorder.[6] Among them, 75% experienced moderate to severe psychological stress, which underlines a need for immediate support. Such a need has not been met owing to the low accessibility and availability of counseling services. The Princeton Review in 2024 revealed the increased rates of students suffering from stress but only 56% of the students were counseled, while 44% did not have any support.[7] This indicated an urgent need for broader service delivery and support to aid in recovery from mental distress and significant improvement in mental health services for college students. Colleges have become aware of the importance of students' welfare and their mental health and have been offering support programs through peers and group therapy. However, individualized support is still lacking.[8] Owing to their preference for mobile technology and online services, students favor telemedicine programs for easier access and a more efficient monitoring of mental health than traditional offline programs.

Colleges are still slow to provide services and help those who have mental distress owing to a lack of relevant knowledge, ability, and means.[9] It is essential to improve the recognition of the importance of preventive measures and community-engaged initiatives to help them effectively and provide various mental health services and facilities. The University of Cambridge has developed a Mental Health and Wellbeing Plan to remove barriers to counseling and provide directions to students in need.[10] The outcomes have fostered improved learning environments for students to achieve academic and personal success. In addition, cooperation with local healthcare providers allows continuity in services on- and off-campus. However, many problems need to be solved as many colleges have limited budgets and human resources for mental health programs.[11] Following the World Health Organization's recommendations, specific actions need to be taken by colleges to improve the mental health of students.

3. Sensor Technology in Learning

Various sensors are used for engaging and effective learning by collecting data presenting heart rate, activity levels, and stress markers.[12] The data present the biometrics of students and teachers to track their emotional and physical status.[13] Environmental sensors are also used to measure temperature, humidity, noise, and light that affect the level of students' concentration and performance.[14] For instance, appropriate lighting positively affects students' thinking capabilities and attentiveness.[15] Therefore, it is important to design an appropriate class environment for learning and monitoring such factors. Applications using sensor data are widely used. Built-in sensors of smartphones are also used to collect data on the students' positions, interactions with peers, and self-reported emotions. The collected data are used to encourage students to be actively involved in learning. Learning applications with sensor data offer a flexible environment for learning processes.

In experiential learning, various sensors are used. For instance, sensors are used in chemistry classes to gather real-time data such as temperature. Sensors and their real-time data enable students to connect theory and practice and understand science concepts effectively. Sensor technology can also be used to enhance learning efficiency since it provides teachers with information on students' performance and attitudes. For instance, data from wristbands inform teachers about the students' emotions that are clues to understand the degree of enthusiasm and understanding, and if they need help in learning or solving problems. Adaptive learning platforms incorporate such sensor data to evaluate learning and teaching efficiency.[12,13]

In collaborative learning, smartphone-embedded sensors provide data on interactions, emotions, and biometrics of students. For example, motion sensor data is used to evaluate students' interaction in a group. The obtained data is used to make recommendations for developing instruction, enhancing teamwork, and increasing the learning effect. Teachers can use sensor-embedded devices for communication in collaborative learning.

Such sensor data is also used to develop and improve curricula. Classroom practices are complemented with sensors to teach data literacy and analytical skills. Teachers must understand the pedagogical content to teach how sensor data is collected, analyzed, and used. Therefore, teachers need to be trained to learn how to operate sensors and use sensor data. Various learning activities can be designed using sensor data.[11] However, it is necessary to protect students' personal information. To use sensors and sensor data in education, teachers and engineers must cooperate to develop educational equipment that meets curricular requirements.

4. Sensor Technology in Early Warning Systems

Sensor technology in early warning systems for mental health addresses issues from behavioral, physiological, and social perspectives. Continuous monitoring allows for immediate interventions for those experiencing mental health problems. Sensor technology is applied to wearable devices, mobile applications, and smart devices. Smartwatch and fitness trackers that are widely used nowadays measure heart rates, sleep patterns, and activity levels using accelerometers and gyroscopes (Fig. 2).[16] HRV can be used to monitor emotional status as it is an indicator of anxiety or depression.[17]

Mental health can be monitored using mobile applications that can report users' moods, stress levels, and psychological signals. The applications are available on smartphones, and the monitored data can be integrated with the location of a person and the person's social networks.[18] The data of the global positioning system indicates the frequency of social interactions, and social networks show individualized feedback and follow-ups of peers and families. The data from those applications can be used to assess how actively or passively the user interacts with others and if the user shows any symptoms of mental distress. Figure 3 shows the currently available applications for mental health monitoring on the market.

Environmental sensors provide data to detect and measure biometrics that are related to mental health. Data that possibly affects an individual's mental health can be provided. For instance, noise heightens the stress level and weather affects emotional status. Wearable devices with such sensors can be used to monitor anxiety or depression using various sensed data.[16] The data collected from the various sensors of the wearable device are used to create AI models to assess and predict the mental health of the user. The model's algorithm identifies potential risks based on the learned patterns from the collected data or abnormality.[19] Li has developed a

Fig. 2. (Color online) Wearable device and sensors included in it.

Fig. 3. (Color online) Available mental health apps.

real-time psychological stress detection system using a pulse acquisition module that quantitatively measures stress levels based on physiological signals.(19) The system prevents the aggravation of mental health problems for timely intervention.

Sensor technology is also used to improve the conventional treatment of mental distress. Therapists design and recommend personalized exercise programs based on real-time data obtained from the wearable device. Such data-driven programs enhance therapeutic outcomes since they allow physicians, nurses, or caregivers to make the right decisions on the basis of the user's behavior and personality. They also enhance the user's involvement in their treatment processes.

5. Predictive Model for Early Intervention

Mental health risk assessment enables accurate predictions of psychological disorders. Predictive models predict mental distress by incorporating the data measured from wearable devices and past data. Using machine learning techniques, the models analyze the data and predict possible symptoms related to anxiety and depression, thereby identifying those who need help and improvement in mental health (Fig. 4).

The predictive models have processes of data acquisition, feature extraction, and data analysis. The data gathered from sensors from wearable devices and a questionnaire survey are used in the model. Saito *et al.* used the biometric data (three months of sleep-wake cycle, physical activity, and resting heart rate data) obtained from wearable devices to assess the probability of developing a mental disorder for the next three months.[20] They used extreme gradient boosting (XGBoost) to construct the model to predict the onset of mental illness.

In the predictive model, feature selection is essential to predict mental health status and improve the model prediction accuracy. In Saito *et al.*'s model, sleep patterns and sleep abnormalities were used as a precursor for the development of disorders and selected as an important feature. Features need to be seriously selected to elucidate the present state of mind and possible signs of an upcoming crisis.

Data analysis is conducted using an algorithm that performs regression analysis, makes decision trees, and creates neural networks. XGBoost is one of the most promising algorithms because it handles large datasets without overfitting.[21] Predictive models need the integration of multiple algorithms for reliable data analysis.

Other than the predictive model, a questionnaire survey is conducted to evaluate and detect anxiety and depressive disorders. The result can provide sensitive and specific data especially

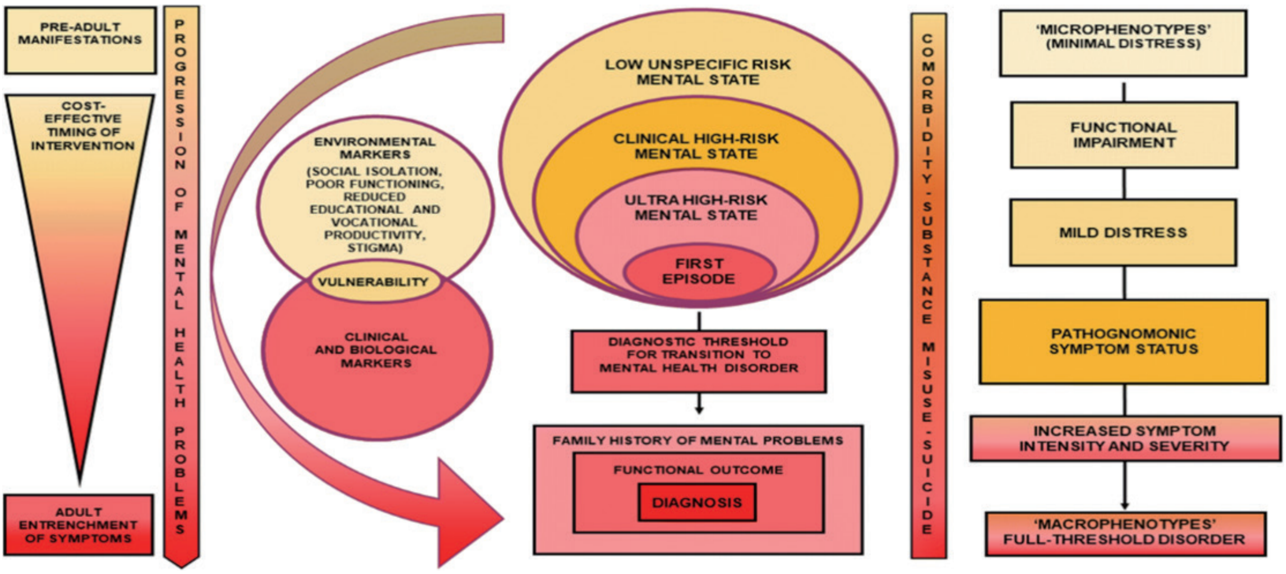

Fig. 4. (Color online) Predictive model to diagnose high-risk mental health status.

for "at-risk" students through the self-assessment of mental health. The survey data need to be integrated with the predictive model to formulate intervention strategies. For example, after a student is identified as a potential risk using a predictive model, counselors need to offer appropriate resources to identify the real issues of the student.(22) This preemptive approach increases students' participation in therapeutic activities on campus. The integrated data enables timely assistance and intervention more effectively(23) and the prevention of worsening mental health.

Such interventions' effects on the improvement of mental health are significant. The development of technology allows algorithms to predict potential mental health problems more accurately on the basis of more collected data. However, challenges such as privacy and ethical issues in data collection and utilization must be addressed as personal information must be required in the prediction process of the model.(11) The generalizability of the predictive model for widespread use needs to be enhanced as the current model performs well for individuals with diverse disorders.(24) By incorporating user feedback on design and implementation, the ease of using the system can also be improved. Lastly, opinions and clinical tests of clinicians and counselors must be reflected in improving the model. The results of the models must be analyzed by them for practical interventions.(25)

6. Implementation of Sensors in Education

We surveyed the efficacy of the prediction in assessing mental health with sensor technology with 100 respondents using a questionnaire. The survey was carried out from December 2023 to December 2024. The questionnaire was created to assess the respondents' experiences with mental health indicators, engagement with sensor technology, and their feedback on the effectiveness of sensor technology. The respondents were randomly selected from the students of Wenhua College in China. The survey was conducted online. The survey results were used for frequency analysis, correlation analysis, analysis of variance, and reliability measurement to identify the interconnection among the indicators of mental health status, sensor technology, and feedback on the effectiveness of sensor technology. The results were compared with those in previous studies to better understand the outcomes of incorporating sensor technology to improve students' mental health.

6.1 Reliability of survey

The reliability of the survey was tested using Cronbach's alpha. The mean was 0.868 for 15 items. While a Cronbach's alpha above 0.70 is generally acceptable, a value higher than 0.80 for the survey in this study indicated high reliability and consistency.(26) The results validated that the questionnaire survey results presented statistical significance.

6.2 Descriptive statistics

The descriptive statistics regarding mental health indicators, engagement with sensor technology, and feedback on the effectiveness of sensor technology were determined. The mean score for mental health indicators was 3.568 [standard deviation (*SD*) = 0.526], indicating a moderate level of mental health concerns among students. The mean score for the engagement with sensor technology was 3.634 (*SD* = 0.461), suggesting that students generally engaged positively with sensor technology for mental health monitoring. Finally, the mean score for feedback on the effectiveness of sensor technology was 3.668 (*SD* = 0.590), reflecting a favorable perception of using sensors in supporting mental health (Table 1). While the respondents experienced mental health problems, they considered that engagement and positive feedback regarding sensor technology helped address these issues. In addition, the respondents recognized the importance of mental health monitoring and were keen on utilizing sensor technology as a supportive tool.

6.3 Correlation analysis

To explore the relationships among mental health indicators, engagement with sensor technology, and feedback on the effectiveness of sensor technology, correlation analysis was performed (Table 2). A positive moderate relationship was observed between mental health indicators and engagement with sensor technology. The higher the engagement with sensor technology, the better the mental health of the respondents (r = 0.559, p < 0.001). This finding

Table 1
Descriptive statistics of questionnaire survey.

Item	*N*	Mean	*SD*	Variance
Mental health indicator	100	3.5680	0.52626	0.277
Engagement with sensor technology	100	3.6340	0.46105	0.213
Feedback on effectiveness of sensor technology	100	3.6680	0.58962	0.348
Number of responses	100			

Table 2
Results of correlation analysis.

		Mental health indicator	Engagement with sensor technology	Feedback on effectiveness of sensor technology
Mental health indicator	Pearson correlation coefficient	1	0.559**	0.368**
	Two-tailed significance		0.000	0.000
	N	100	100	100
Engagement with sensor technology	Pearson correlation coefficient	0.559**	1	0.732**
	Two-tailed significance	0.000		0.000
	N	100	100	100
Feedback on effectiveness of sensor technology	Pearson correlation coefficient	0.368**	0.732**	1
	Two-tailed significance	0.000	0.000	
	N	100	100	100

**Significance level of 0.01.

aligns with that of Lehtimaki *et al.*,[27] who also noted that students who used digital mental health services experienced less anxiety and depression. The use of sensor technology enhanced college students' mental health, thereby supporting educational institutions' adoption of the technology.

Mental health indicators had a moderate positive correlation with the feedback on the effectiveness of sensor technology ($r = 0.368$, $p < 0.001$). The respondents who considered sensor technology effective had better mental health status. Perceived effectiveness by the respondents for technology enabled the achievement of mental-health-related goals.[28] Such a relationship indicated the need to integrate sensor technology to understand its potential for mental health support. Consequently, colleges need to fine-tune the student's experience to prove the value of the technology to enhance the acceptance and adoption of sensor technology.

In addition, a highly positive relationship existed between engagement with sensor technology and feedback on the effectiveness of sensor technology ($r = 0.732$, $p < 0.001$). The more the respondents used sensor technology, the better their impression of its effectiveness. Such a relationship is related to a positive perception of effectiveness and the frequency of use. When wearable devices were used to gather data in real time, the user's psychological well-being was improved.[29] Therefore, colleges must ensure that students find sensor technology interesting and useful for the well-being of the students. The results of correlation analysis showed positive correlations between mental health, sensor technology, and efficiency in managing mental health. Therefore, it is necessary to encourage the use of sensor technology for mental health management.

6.4 ANOVA results

The total sum of squares was 27.418 with an F-value of 22.427, which was significant at $p < 0.001$ (Table 3). This implied that engagement with the sensor technology and feedback on the effectiveness of sensor technology were used to assess the usefulness of mental health status indicators. The result coincided with that of a previous study and indicated the need to implement sensor technology for mental health monitoring.[30] A high F-value implied that the engagement with sensor technology and perceived effectiveness impacted mental health, and colleges must emphasize the user-centered approach in designing the early warning system with sensor technology.[31] Depending on the respondents, the level of engagement and the perceived effectiveness of sensor technology varied,[32] which necessitates further studies to better understand how to use sensor technology to satisfy the user's requirements. Sensor technology

Table 3
ANOVA results.

Model		Sum of squares	*df*	Mean square	*F*	Sig.
	Regression	8.669	2	4.335	22.427	0.000[b]
1	Residual	18.748	97	0.193		
	Total	27.418	99			

[a]Dependent variable: mental health indicators.
[b]Predictor: feedback on effectiveness of sensor technology, engagement with sensor technology.

and its effective feedback by users affect the mental health status of college students. Therefore, the result of ANOVA underscores the necessity for students to use sensor technology to improve their mental health. Hence, colleges need to enable students to benefit from technology and to enhance their mental health.

6.5 Discussion

The results of this research demonstrate the importance of sensor technology in helping college students with mental health problems. The positive relationship between engagement with sensor technology and mental health status proved that the students who used the early warning system with sensors had better mental health than those who did not use it. This finding coincided with that of Borghouts *et al.*,(31) which indicated that students using digital mental health resources had reduced anxiety and depression. The implementation of sensor technology and the early warning system using it helped students improve their mental health. Therefore, colleges need to promote the early warning system to help students improve and maintain their mental health. Active feedback on the effectiveness of sensor technology was crucial for technology usage as it enhanced user perception. Students considered that the system improved their mental health. This aligned with Garavand *et al.*'s research result,(33) who noted that the perceived effectiveness of the technology is most important for mental health conditions. In improving the utilization value and positive impact of sensor technology, technology acceptance by students and colleges is important. Therefore, colleges must encourage students to use the system for better mental health. The degree of engagement and feedback on effectiveness are precursors of mental health. The positive experience and perceived effectiveness of sensor technology explained differences in mental health status. The results presented the importance of adopting a user-centered system in mental health applications.(34) Given the growing interest in implementing best practices for students, there is a need to understand the interrelations of engagement and feedback on the system and examine factors affecting the use of the system.

However, several limitations need to be addressed. There might be a bias owing to exaggerating mental health status due to social desirability. In future research, quantitative data need to be gathered by monitoring the clinical status of mental health. As the survey in this study has been conducted for students from a particular social background, a larger number and a more diverse population of students need to participate in the survey.

In this study, how sensor technology and the system using it affected the mental health status of college students was elucidated. As active engagement and feedback on the system and the effectiveness of the system affected students' mental health, colleges need to encourage students to be active in using the system.

7. Conclusion

By applying sensor technology and developing a system, students can improve their learning effectiveness as well as mental health. In different scenarios, the applications of sensor technology and the system using it need to be studied to enhance students' performance and engagement in various activities. Nevertheless, it is not easy to implement such technologies, and it is necessary to consider data privacy, data security, expertise, consent, compatibility, and cost, which are the issues that must be addressed. Sensor technology and related systems require further research. On the basis of the results of this study, teachers, policymakers, and stakeholders must collaborate for the establishment of guidelines regarding the ethical application of advanced technologies to enhance student learning experiences and achievement.

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