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An Intelligent IoT Framework for Early Identification of stress Among University Students using Machine Learning

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Abstract - Stress is among the common problems that confront college students and may impact their educational and learning results, emotional state, and life quality. Stress assessment has traditionally relied on the use of self-report psychological tools that offer valuable, but infrequent data about a person's stress state. The proposed framework in this study, IoT-StressNet, is an intelligent framework that integrates DASS-21 psychological stress assessment with machine learning and a proposed Internet of Things (IoT) layer for future continuous monitoring. This study uses the Stress subscale of DASS-21 to calculate the students' stress level, and then multiple machine-learning algorithms, such as Logistic Regression, Support Vector Machine, Random Forest, K-Nearest Neighbors, Gradient Boosting and ensembles are used to analyze the stress level. The model with the best performance from the tested methods in terms of the accuracy was the Optimized Stacking model with 98.237%, precision of 98.081%, recall of 98.00% and F1 of 97.80%. These findings show the effectiveness of machine learning in detecting stress-related patterns in psychological assessment data. Based on this analytical basis, IoT-StressNet foresees the future integration of wearable sensor systems, smartphone sensors, IoT communication, cloud/edge analytics and decision support mechanisms for continuous monitoring of stress. Privacy, interoperability, scalability and ethical considerations for responsible deployment of the framework in smart campus environments are also taken into consideration.

Index Terms— IoT, Mental Health, Machine Learning, DASS -21, Stress

I. INTRODUCTION

Stress is one of the most prevalent psychological problems of university students today. Stress during college is often caused by academic workload, exam stress, financial pressures, career path uncertainty, family pressures, and social adjustment. Extended stress, if unaddressed, can have a negative impact on students' physical health, emotional well-being, cognitive functioning, academic achievement and quality of life (World Health Organization [WHO] 2022). The early detection of stress is an emerging research focus in education and health and is vital for early intervention, psychological support and enhancing student well-being in educational institutions and health-care settings.

The traditional methods of stress assessment include self-administered questionnaires, psychological interviews and periodic clinical assessments. Stress is measured using standardized assessment instruments, for instance the Depression Anxiety Stress Scale (DASS-21), which has been found to be reliable and valid in a range of populations (Lovibond & Lovibond, 1995). These conventional approaches, however, measure stress as a single event and are almost entirely based on self-report, which can be affected by recall bias, emotionality and/or a reluctance to report personal experiences. Therefore, early physiological changes and stress level fluctuations can often go unnoticed, and intervention is often delayed.

The Internet of Things (IoT) has introduced new opportunities for intelligent healthcare systems that can be used for continuous monitoring of physiological and behavioral conditions in recent years. The given Figure 1 shows the proposed IoT-StressNet framework for identifying stress among University students.It incorporates DASS-21 assessment, wearable/smartphone sensing and IoT-based data communication.The collected information is analyzed by using cloud and AI to categorize the stress as low, moderate or high.

The framework can be used for early intervention, personalized guidance and proactive student stress management.The parameters that can be measured by wearable devices and wearable sensors are potentially heart rate, heart-rate variability (HRV), sleep parameters, physical activity, blood oxygen saturation (SpO_2), and skin temperature. Likewise, smartphones can deliver behavioral data on the patterns of use, applications, mobility, and daily use. The use of such information has been explored in recent studies as a source of stress-related indicators (Cornet & Holden, 2022; Dias et al., 2023). In the present study, however, these IoT-generated signals were not measured but are proposed.

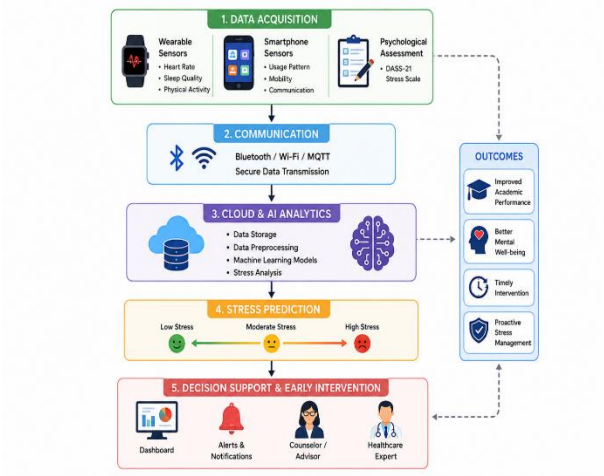


Fig. 1. IoT StressNet Framework for Stress Identification.

The application of Artificial Intelligence (AI) and Machine Learning (ML) opens the door to studying complex relationships between psychological, physiological and behavioral data. Psychological and wearable-derived data have been tested for stress identification with the application of machine learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB) and ensemble methods (Abd-Alrazaq et al., 2024). In the current study, these methods are used to analyze student data from the DASS-21 questionnaire to reveal patterns of stress. This proposed addition of the IoT component will further extend this

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analysis in the future by adding continuous physiological and behavioral sensing.

The Internet of Things is really helpful for checking stress levels. There are still some problems that we need to solve. A lot of studies only look at the data, from devices that track our bodies. They do not think about the information that we can get from our smartphones about how we behave. On the hand some studies only ask people questions and do not use special tools that can track things all the time. We also have to deal with some issues like making sure all the different Internet of Things devices can work together keeping the data safe when we send it protecting people's privacy making sure the cloud can handle a lot of data and making sure the computer programs that learn from data can explain what they are doing. Internet of Things devices and stress monitoring systems are affected by these problems. This means we need a system that can put together all the kinds of information we have and make sure it is safe and reliable when we are trying to figure out if someone is stressed. Internet of Things and stress monitoring systems can be very helpful if we can make them work better.

To overcome these problems, this paper presents an intelligent IoT oriented framework, called IoT-StressNet, for detection of stress condition among university students through machine learning. In the present study, the psychological assessment was carried out using the DASS-21 questionnaire as the main source for determining stress and assessing various machine learning models for the effectiveness of stress identification. The framework suggests wearable and smartphone-based sensing, IoT communication, cloud/edge analytics, and decision-support mechanisms can be integrated in the future to support continuous monitoring of stress. The proposed framework is intended to be a foundation for the proactive stress management and smart campus healthcare, taking into account privacy, security and ethics needs.

The major contributions of this paper are summarized as follows:

- Proposes IoT-StressNet, which is an intelligent framework for early stress detection in university students.
- Implements as main approach for the stress identification the DASS-21 Stress assessment and machine learning.
- Compares several machine learning and ensemble models in learning student stress patterns.
- Suggests the extension of future continuous monitoring for stress using wearable and smartphone sensing as an IoT based one.
- Designs an IoT-based architecture including cloud/edge analytics, dashboards, warning systems, and ethical issues, as well as scalability and privacy issues.

II. LITERATURE STUDY

In recent years, studies focusing on wearable sensors, Internet of Things (IoT) and machine learning have gained momentum for stress identification over time. Wearable systems can also produce physiological data continuously, and can be used to detect stress in the real world as opposed to the laboratory setting of traditional questionnaires.

Tazarv et al. (2021) have explored the concept of customized stress monitoring in real-world contexts, leveraging the use of wearable sensors. They employed an HRV/HR-based methodology that relied on photoplethysmography, which concluded the feasibility of personalized stress detection in field settings. The study was conducted with a limited number of participants, however, and has limited generalizability.

Gedam and Paul (2021) summarized the methods for stress detection using wearable sensors and emphasized the increasing trend of using physiological signals (ECG, EEG, PPG) with machine learning. They noted that continuous stress monitoring can be enhanced by having multiple modalities of sensors and using intelligent algorithms, but variations in data and experiments can still pose challenges.

Garg et al. (2021) have tested a number of machine learning algorithms with the WESAD wearable dataset. Their findings showed that Random Forest was effective to classify stress and highlighted the potential of machine learning to identify physiological stress. However, the use of a benchmark dataset restricts the application of directly translating to real student environments.

Rashid et. al (2022) have presented a selective sensor-fusion strategy with context-awareness that aims to save power in wearable stress monitoring systems. They showed that when selecting sensors based on context, high classification accuracy can be obtained with high energy efficiency, which is essential for wearable devices in IoT.

The generalizability of machine-learning methods for stress monitoring through wearable devices was investigated by Vos et al. (2022). They found that small data sets, inconsistent ground truth definitions and limited cross-person validation were significant issues. This shows that a good performance on one set of data does not necessarily imply good performance on a different population.

Razavi et al. (2023) conducted a study specifically targeting stress among college students, utilizing wearable sensors to capture heart-rate and hand-acceleration data. The results showed that physiological data from wearables can be leveraged to identify student stress, with XGBoost being a particularly effective algorithm. However, the study's limitation includes a small sample size and the use of self-reported stressful events.

Abd-Alrazaq et al. (2024) performed a systematic review and meta-analysis of the use of wearable AI in detecting student stress. The researchers evaluated nineteen (19) articles and concluded that the pooled mean accuracy of wearable AI in detecting student stress is at 85.6%. The results highlight the potential of wearable AI in detecting student stress but also reveal the heterogeneity of the included studies, ranging from the type of devices, data sets, stress categories, and ground-truth labeling criteria (Abd-Alrazaq et al., 2024).

Neigel et al. (2024) conducted a study among university students to examine stress using a novel approach of employing a ring-shaped wearable sensor. The results showed significant variations in physiological stress indicators around exams and other stressful events, illustrating the potential of minimally invasive wearable sensors in capturing student stress. However, the study's limitation was that the focus was on group-level trends rather than individual-level predictions.

Finally, a study by Ta et al. (2025) focused on real-time student stress detection and management among college students using wearable sensors and machine learning. The study went beyond simply detecting stress and showed how IoT-based solutions can help manage and alleviate student stress in real-time.

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The given Table 1 summarizes recent research that have been done on using wearable sensors, internet of things (IoT) and machine learning for stress and mental health monitoring.

The majority of studies show that physiological data like heart rate and heart-rate variability can be used in stress detection.Ensemble and tree-based models have demonstrated good classification accuracy in various datasets, highlighting their potential in machine learning applications.

Despite this, certain weaknesses of past research, such as small samples, self-report, inconsistent methods, and limited in vivo validation are prevalent.In general, prior research has established the potential of utilizing wearable sensors and machine learning for continuous stress recognition. However, limitations regarding multiple modalities, real-world student validation, privacy, interoperability, and end-to-end IoT architectures still persist. Prior work has focused on physiological sensing or machine learning-based classification rather than an integrated solution that combines sensing, communication, cloud-based analytics, prediction, and decision-support within an IoT-based architecture. This paper introduces IoT-StressNet, an integrated IoT-based architecture for continuous stress identification in university students.Table 1 Summarize the recent research on IoT wearable Technologies and machine learning algorithm for the early prediction the stress.

TABLE I. Summary of Selected Study on IoT and Machine Learning

Author(s)	Year	Technology Approach	Major Finding	Limitation
Tazarv et al.	2021	Wearable sensors, HR, HRV	Demonstrated personalized stress monitoring	Small sample
Gedam & Paul	2021	Wearables + ML	Identified promising physiological biomarkers	Methodological variation
Garg et al.	2021	WESAD + ML	RF showed strong stress-classification performance	Benchmark dataset
Rashid et al.	2022	IoT + selective sensor fusion	Improved energy-efficient stress detection	Limited real-world validation
Vos et al.	2022	Wearable ML review	Highlighted generalizability problems	Review-based study
Razavi et al.	2023	Smartwatch + XGBoost	Demonstrated stress identification among college students	Small sample/self-report
Abd-Alrazaq et al.	2024	Wearable AI + ML	Pooled accuracy ≈85.6% across student studies	Heterogeneous studies
Neigel et al.	2024	Wearable ring	Identified stress patterns during academic periods	Mainly population-level analysis
Saylam et al.	2024	Wearables + multitask ML	Demonstrated potential of wearable digital biomarkers	Broader mental-health scope
Ta et al.	2025	Wearable + mHealth + ML	Demonstrated real-time stress monitoring/intervention	Further validation needed

The literature review suggests that wearable sensing and machine learning are effective to recognize stress, the majority of the studies rely on a small number of datasets and utilize a certain sensing technology. There is a research gap to develop a framework which integrates wearable physiological sensing, smartphone-based information, IoT communication, cloud analytic services, machine learning, and instant visualization for decision-making, particularly for university students. This is the rationale for developing IoT-StressNet.

III. PROPOSED METHODOLOGY

The proposed IoT-StressNet framework combines psychological stress assessment, machine learning, and an IoT-based sensing architecture for the early identification of stress among university students. In the present study, the DASS-21 Stress subscale is used as the primary psychological measure of student stress. The proposed IoT layer extends this analysis by introducing wearable and smartphone-based sensing for continuous monitoring. This design is motivated by recent studies showing that physiological indicators obtained from wearable devices can be associated with perceived stress among university students (Bloomfield et al., 2024).

The figure 2 shows the proposed framework of using DASS-21 and machine learning for stress identification among University students. These involve stress assessment, score computation, data pre-processing, feature engineering, and using machine learning for classification. The proposed IoT layer brings HR data, HRV data, sleep data, EDA data and activity data together via an IoT gateway for cloud/edge analytics. The framework will help to identify stress in real time and facilitate monitoring and early warning through the dashboard.

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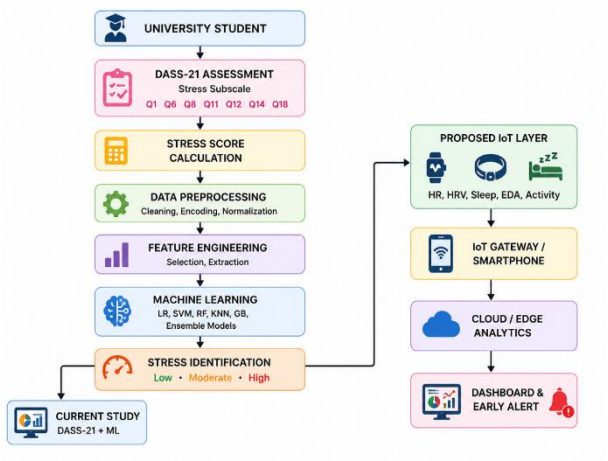


Fig. 2. The proposed methodology of IoT-StressNet for stress identification based on DASS-21

A. PHYSIOLOGICAL STRESS ASSESSMENT USING DASS-21

The main psychological variable used as the basis for this study is the Depression Anxiety Stress Scale-21 (DASS-21). In particular, even though the DASS-21 consists of three subscales, the study focuses only on the stress subscale as the main variable for identifying stress among participants. Indeed, there are several items within the stress subscale, including Q1, Q6, Q8, Q11, Q12, Q14, and Q18. The seven DASS-21 stress subscale items (Q1, Q6, Q8, Q11, Q12, Q14, and Q18) are summed and the resulting subscale score is multiplied by two to obtain the conventional DASS-21 stress score (Lovibond & Lovibond, 1995). which presents a standardized manner of recording the severity of symptoms of depression, anxiety, and stress. In the same manner, within this framework, the DASS-21 score is considered the most relevant variable in terms of machine-learning-based stress identification. However, it is important to note that the DASS-21 score only serves as a screening and assessment tool, not a definite diagnostic procedure, which must be conducted by qualified healthcare professionals.

B. DATASET PREPARATION

After collecting the student's responses, they need to be reviewed for validity, reliability, and completeness. The data set with responses that does not meet the criteria will be deleted for research analysis. Finally, the collected data set will be formed into a structure that will contain the DASS-21 Stress items alongside other relevant student characteristics identified in the study.

Furthermore, the data will need to be prepared for the machine learning procedure. The data set will be cleansed, with categorical variables being encoded and numerical variables normalized. Preprocessing becomes essential since the variance across variables, irregularities, and noise impact the performance of most classification algorithms.

C. STRESS SCORE CALCULATION

The seven DASS-21 Stress items can be used to calculate an individual stress score. According to the standard DASS-21 scoring procedure, the score of the subscale is multiplied by two to obtain an individual stress score if the conventional DASS-21 scoring interpretation is used (Lovibond & Lovibond, 1995).

The obtained score can then be used to determine the severity of stress according to the DASS-21 scoring guidelines. The stress category is then used as the target variable for the machine-learning stage.

The conceptual link can be represented as follows:

DASS-21 Stress Items → Stress Score → Stress Category → Machine Learning Classification

This provides the theoretical basis for the proposed system for stress identification.

D. DATA PREPROCESSING AND FEATURE ENGINEERING

Before developing the models, it is essential to preprocess and engineer the data to obtain high-quality input. The following steps are considered during this stage:

- Removal of duplicates and irrelevant data records.
- Checking and treating of missing values.
- Encoding of categorical variables.
- Normalization and scaling of variables, where necessary.
- Feature selection and engineering.

In the case of stress, the last step is especially critical since the relevant features could be different for each person. According to one of the articles about wearable stress detectors, having several physiological measurements could be more informative than using a single sensor (Ninh et al., 2022).

E. ALGORITHMS

The resulting dataset can be used to train supervised machine-learning models for the task of stress classification. Based on the final design of the experiment, the study can compare the performance of different algorithms, including but not limited to the following options:

Logistic Regression (LR)
Support Vector Machine (SVM)
Random Forest (RF)
K-Nearest Neighbors (KNN)
Gradient Boosting (GB)
Ensemble learning

The trained model can classify students based on the selected features, with DASS-21 categories used as a ground truth reference. The performance of the model can be evaluated with scalar metrics, such as accuracy, precision, recall, F1-score, and ROC-AUC. In addition, a confusion matrix can be used to evaluate the performance of the classifier for each category and compare the rates of true and false predictions.

The application of machine learning to classify the stress levels of students with wearable sensors has been demonstrated in previous studies. In his article, Chandra and Sethia (2024) describe an algorithm that processes EEG, electrodermal activity, skin temperature, and heart rate data from various types of wearable sensors to classify students into rest, moderate, and high-stress categories based on physiological data.

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F. INTEGRATION OF PHYSIOLOGICAL DATA AND DASS-21

The fundamental idea of IoT-StressNet revolves around the concepts of psychological assessment, namely, continuous sensing. Specifically, DASS-21 is utilized as the psychological reference standard in the current study, whereas, in the future IoT application, physiological and behavioral sensing can be integrated with such a psychological reference to better identify the stress state on an individual level.

The combined framework can be visualized as follows:

DASS-21 Psychological Assessment ⇒ Stress Reference
Wearable/Smartphone Sensing ⇒ Continuous Physiological & Behavioral Indicators
Machine Learning ⇒ Stress Identification

which aims to address the limitation mentioned by Abd-Alrazaq et al. (2024): while wearable AI demonstrates promising results for student stress recognition, the current solution is recommended to be integrated with established assessment procedures until more robust empirical evidence becomes available.

G. DECISION SUPPORT SYSTEM

The final level of IoT-StressNet is the decision-making level, through which it is possible to represent a forecasted stress state in the form of a digital dashboard. The proposed dashboard can visualize the current level of stress and the associated changes in physiological or behavioral indicators. In case of detecting a consistently high level of stress, the system is designed to notify the student and, with consent, the university counseling service of an early warning.

The system is designed to ensure early intervention and thus help in decision-making rather than provide diagnostic conclusions. It is especially important to emphasize that this is a supportive tool, and decisions about the level of stress must be made by healthcare professionals.

IV. RESULTS AND DISCUSSION

The proposed machine-learning method was trialed on the DASS-21 Stress subscale to determine stress-related patterns among university students. The models used for classification include KNN, SVC, Random Forest, Gradient Boosting, Logistic Regression, Optimized Stacking, and Optimized Voting algorithms.

The Optimized Stacking achieved the maximum accuracy of 98.237%, with 98.081% precision, 98% recall, and 97.8% F1-score. The second-best model was Logistic Regression with 97.40% accuracy, followed by the Optimized Voting algorithm with 97.03% accuracy. Thus, the results demonstrate that applying ensemble learning is a feasible approach to identifying patterns specific to student stress.

The table 2 lists the accuracy, precision, recall, and F1 score of the various machine learning and ensemble models for the stress classification task. In all models, the highest accuracy performance was observed for Optimized Stacking which had 98.237% accuracy and gave better and consistent classification performance than individual and voting models

The results of the present work align with the past research that showed the potential of machine learning and wearable sensing based on IoT for student stress identification (Bloomfield et al., 2024; Chandra & Sethia, 2024). In the present study, however, we did not have the opportunity to directly apply the wearable sensors to measure the stress level, but rather, we used the DASS-21 psychological assessment instrument and machine learning approaches for stress identification. In the present study, the proposed IoT component (physiological parameters: HR, HRV, sleep, EDA and physical activity) has not been experimentally tested. The machine-learning models achieved satisfactory classification accuracy, high precision, recall, and F1-scores, which means they are effective in distinguishing between stress patterns based on the assessment data collected. Thus, the results give early validation for the proposed framework and further work with real-time (IoT) wearable-based sensing should be conducted to validate and enhance it in real-world scenarios.

TABLE II. Result of algorithms

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
KNN	76.01	75.03	77.02	77.03
SVC	96.03	97.01	97.12	97.12
Random Forest	76.01	76.10	75.12	76.01
Gradient Boosting	73.20	74.18	73.02	73.00
Logistic Regression	97.40	96.32	97.18	97.24
Optimized Stacking	98.237	98.081	98.00	97.80
Optimized Voting	97.03	96.02	97.25	96.25

V. CONCLUSION

This study proposed IoT-StressNet, an innovative concept for stress recognition among university students by leveraging the power of the DASS-21 psychological survey, machine learning algorithms, and a novel approach to IoT (Internet of Things) sensing. The results of this study suggest that the application of machine learning to the task of recognizing stress patterns in students is indeed viable and can yield accurate results. This was demonstrated by classifying the data set of students with stress patterns using multiple machine learning models, with the Optimized Stacking model achieving an impressive accuracy of 98.237%. In addition, the proposed architecture provides a conceptual basis for developing an always-on, always-accurate system for tracking and analyzing behavioral patterns related to stress, utilizing wearable sensors and smartphone data. The latter aspect, namely, the use of IoT for stress monitoring, has not been empirically validated in this study and may be the subject of future research. By and large, this study has provided a viable basis for creating an intelligent system for

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stress recognition in students, which could form the basis for a truly smart campus in the future.

REFERENCES

[1] Razavi, M., McDonald, A., Mehta, R., & Sasangohar, F. (2023). Evaluating mental stress among college students using heart rate and hand acceleration data collected from wearable sensors. arXiv. https://doi.org/10.48550/arXiv.2309.11097

[2] Tazarv, A., Labbaf, S., Reich, S. M., Dutt, N., Rahmani, A. M., & Levorato, M. (2021). Personalized stress monitoring using wearable sensors in everyday settings. In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 7332–7335). IEEE. https://doi.org/10.1109/EMBC46164.2021.9630224

[3] Vos, G., Trinh, K., Sarnyai, Z., & Rahimi Azghadi, M. (2022). Generalizable machine learning for stress monitoring from wearable devices: A systematic literature review. arXiv. https://doi.org/10.48550/arXiv.2209.15137

[4] Ta, A., Salgin, N., Demir, M., Reindel, K. P., Mehta, R. K., McDonald, A., McCord, C., & Sasangohar, F. (2025). Real-time stress monitoring, detection, and management in college students: A wearable technology and machine-learning approach. arXiv. https://doi.org/10.48550/arXiv.2505.15974

[5] Bloomfield, L. S. P., Fudolig, M. I., Kim, J., Llorin, J., Lovato, J. L., McGinnis, E. W., McGinnis, R. S., Price, M., Ricketts, T. H., Dodds, P. S., Stanton, K., & Danforth, C. M. (2024). Predicting stress in first-year college students using sleep data from wearable devices. PLOS Digital Health, 3(4), e0000473. https://doi.org/10.1371/journal.pdig.0000473

[6] Chandra, V., & Sethia, D. (2024). Machine learning-based stress classification system using wearable sensor devices. IAES International Journal of Artificial Intelligence, 13(1), 337–347. https://doi.org/10.11591/ijai.v13.i1.pp337-347

[7] Lovibond, P. F., & Lovibond, S. H. (1995). The structure of negative emotional states: Comparison of the Depression Anxiety Stress Scales (DASS) with the Beck Depression and Anxiety Inventories. Behaviour Research and Therapy, 33(3), 335–343. https://doi.org/10.1016/0005-7967(94)00075-U

[8] Ninh, V.-T., Nguyen, M.-D., Smyth, S., Tran, M.-T., Healy, G., Nguyen, B. T., & Gurrin, C. (2022). An improved subject-independent stress detection model applied to consumer-grade wearable devices. In IEA/AIE 2022: Advances in Artificial Intelligence (pp. 907–919). Springer. https://doi.org/10.1007/978-3-031-08530-7_77

[9] Calbert, L., & Hashemi Tonekaboni, N. (2024). Temporal dynamics of classroom stress: Insights from wearable sensors and machine learning. In 2024 International Conference on Machine Learning and Applications (ICMLA). IEEE. https://doi.org/10.1109/ICMLA61862.2024.00057

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