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STATE-AWARE HUMAN ACTIVITY RECOGNITION USING MULTI-MODAL TIME-SERIES PHYSIOLOGICAL AND MOTION SIGNALS FOR MONITORING FATIGUE, STRESS, AND CHRONIC HEALTH CONDITIONS IN PAKISTAN

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Abstract
The aim of this study is to examine the effectiveness of a state aware HAR framework that incorporated multiple types of physiological signals (HR, HRV, PPG, and skin temperature) and motion (Accelerometer and Gyroscopes). Physiological, Motion, and Video datasets were collected from 120 Adult Subjects in Punjab and Sindh under both controlled (n=80) and Free-Living (n=120) research conditions, resulting in 8720 hours of data and 512340 usable time windows; all datasets were processed through Butterworth and Adaptive filtering methods, followed by early and late stage fusing of multimodality data. Model performance was evaluated using a subject independent test and 10-fold cross validation, wherein Hybrid CNN-LSTM models achieved Mean Accuracy and F1 Score of 94.8% (F1=94.8%). On the other hand, state aware ensemble models were able to recognize Stress with Mean Accuracy and F1 Score of 91.2% (F1=91.1%) and Fatigue with Mean Accuracy and F1 Score of 89.7% (F1=89.7%). Chronic Physiological Indicators related to Hypertension and Post-COVID Fatigue were identified at Mean Accuracy = 87.5% (F1 = 87.6%). Pre-processing techniques utilized to reduce Signal Noise by 78%, increase Valid HRV Extraction to 92%, and Fusion between Multi-model modalities (i.e., Acquiring from various cultural sources) improved reductions in average cultural-based Variability of approximately 65%. Overall usability analysis showed a high, (82.4 + 8.6) System Usability Scale score and that 85% of respondents expressed a Willingness to use.

INTRODUCTION

Background of Study

Pakistan faces major public health problems due to Fatigue, Stress and Chronic illness related to urbanization, socio-economic stress and COVID-19. For example, oxidative Stress is a significant contributor for Post COVID 19 chronic fatigues with 65% of patients experiencing chronic fatigue from various Cities e.g. in Islamabad and Rawalpindi Post COVID 19 & also Chronic illness (e.g. Hypertension affects 32% of people with chronic fatigue) indicated a strong link between emotional or mental health and chronic conditions (Govindasamy et al., 2025). In Pakistan, during the COVID-19 pandemic, dialysis patients and their primary caregivers had an increased prevalence of fatigue, anxiety, and depression due to barriers to accessing healthcare and isolation measures (Jaleel et al., 2022). In addition, students studying medicine and healthcare workers throughout the country were also experiencing an increased prevalence of chronic fatigue related to anxiety, depression, and stress, and particularly the increased rates of these disorders were higher among female medical students (Raza et al., 2020). The situation is further complicated by the high rates of both communicable and non-communicable diseases (58% of the overall disease burden) in Pakistan and therefore requiring the development of innovative monitoring approaches that meet the needs of resource-constrained settings (from a web search of prevalence).

Human activity recognition (HAR) is one of the most useful methods to continuously monitor health, using wearables that gather data on your physical, emotional, and mental health to define your current state of health or activity. The existing methods for human activity recognition (HAR) are based mainly on motion signals collected from various types of inertial sensors such as accelerometers and gyroscopes. Using multiple different data modalities (such as elevation profiles of the ground, temperature) together with physiological signals (e.g., heart rate, HRV, PPG), will provide greater accuracy in assessments of subjective experiences of fatigue and stress (Fang & Mushtaque, 2024).

Sansakorn et al. (2024), state-aware human activity recognition (HAR) enhances the model's ability to differentiate between different activities through consideration of the user's physiological state, which may include effects such as stress or fatigue. Researchers have demonstrated this approach's enhanced recognition capabilities with studies using generative models for predicting user activity from motion data. Recent advancements in wearable technologies are providing opportunities for performing real-time analysis on these signals for stress prediction, with the most successful machine-learning models achieved through the combination of inertial and physiological input data (Lazarou & Exarchos 2024). Additionally, AI-based multi-modal methods for monitoring fatigue have been effective in detecting small changes in user physiology through the fusion of multiple sources of data, such as signals collected by wearables, addressing issues such as individual differences and environmental noise (Kakhi et al. 2025; Adão Martins et al. 2021).

Despite many advancements, the majority of HAR uses the Western population or the domains of controlled environments. There is not sufficient research on how cultural, environmental, and infrastructural factors affect health outcomes and signal distributions in low-and-middle-income countries (such as Pakistan) that can limit the impact of HAR studies. In addition, while new datasets that combine multimodal signals have been developed under real world stress and exercise conditions, they have not examined chronic conditions in populations that are counted as diverse. The application of deep learning methods to the task of identifying stress and the use of physiological signal transformations provides exciting possibilities for the development of state-aware systems; however, there remain significant gaps in the ability to integrate these methods for the purpose of chronic health monitoring in Pakistan. This study seeks to address these gaps by creating a state-aware HAR framework that integrates multimodal physiological and motion signals to identify fatigue, stress and chronic conditions in a specifically designed format for the population of Pakistan.

Objectives of Study

1. To collect a complete set of physiological and motion data of Participants from Pakistan under typical situations (normal day-to-day activities, induced stress and fatigue).
2. Pre-process as well as fuse multiple (e.g. physiological) time-series of data while accounting for noise, individual variability and the cultural and environmental contexts in which the data were collected.
3. Assess the capability of the framework to detect fatigue, stress and the early manifestation(s) of chronic disease using standard performance metrics.
4. Determine if the intervention is feasible, usable and culturally appropriate for use in low-resource settings in Public Health in Pakistan.

Methodology

The mixed methods employed in this research are primarily based on quantitative methods, which were used for collecting and analyzing data through the development and evaluation of a state-aware Human Activity Recognition (HAR) system that can monitor fatigue, stress, and chronic health conditions using multiple types of physiological data (multi-modal) and motion data (multi-modal).

Research Desing

The study adopted an experimental research design involving data collection in real-world and controlled settings, followed by machine learning model development and validation. Data were collected from participants in Pakistan to ensure contextual relevance.

Participants

All adult participants were recruited from both urban and semi-urban communities from within Punjab and Sindh provinces in Pakistan using purposeful sampling in addition to snowball sampling. The criteria for inclusion were: (1) the subject can complete typical daily activities; (2) the subject does not have a specific illness at the time of taking part; and (3) the subject is willing to wear a physical activity monitor for an extensive period. The individuals who made up the study sample included individuals who were Healthy (n = 60), Chronic Fatigue/Stressful Individuals (n = 40), and Individuals with Chronic Health Concerns including Hypertension/Post COVID Fatigue (n = 20). Ethics approvals from within the host University's Institutional Review Board; informed consent has been obtained from all study participants.

Data Collection Instruments and Procedure

Wearable devices widely available in Pakistan, including the Garmin Vivo smart 5 or Fitbit Charge 6 wristbands, were provided to participants. These wristbands were able to track physiological signals such as: heart rate and heart rate variability (HRV), photoplethysmography (PPG) derived from heart rate and HRV, and Skin temperature (where available). Additionally, each participant was given a mid-range Android Smartphone (e.g. Samsung Galaxy A-series or Xiaomi Redmi series, which are popular in Pakistan) for tracking motion. Each Smartphone had an Inertial Measurement Unit (IMU) containing both 3-axis Accelerometers and Gyroscopes to collect motion signal data. The sampling frequency for collecting motion signal data from the IMUs was set to the maximum frequency supported by the IMUs (this is typically between 50-100 Hz). The sampling frequency for PPG and HRV could either be continuous or intermittent.

Data Collection Occurred in two phases over a six-month period (January-June 2025):

1. **Controlled phase (n=80):** All participants carried out standardized activities (walking, sitting, standing, and climbing stairs) under conditions of externally imposed stress (the Trier Social Stress Test protocol) and cognitive and physical fatigue (enabled through prolonged cognitive and physical tasks). Pre- and post-task assessments of self-reported fatigue (Fatigue Assessment Scale) and perceived stress (Perceived Stress Scale) were carried out.
2. **Experimental Phase (n=120):** During their usual everyday activities, participants wore wearables for seven to 10 continuous days. Through a mobile application, they reported the activities they engaged in as well as perceived levels of fatigue and stress as requested at random times throughout the day and at the end of each day.

Activity ground truth labels were created from synchronized video recordings (during the laboratory phase) and from participant-created time stamps based on experience sampling while living freely (during the free-living phase). Labeling of physiological states (fatigue/stress) was completed using both validated self-report thresholds and established biomarkers such as lower heart rate variability (HRV) indicating stress.

Data Preprocessing and Feature Extraction

The raw time-series signals were first cleaned with Python libraries. The first step involved removing the "noise" from the signal (via Butterworth low-pass filter). The second step involved removing motion artifact from the PPG signal (via adaptive filtering). Then, all signals were split into 10 second sliding windows with 50% overlap. All multi-modal streams were then synchronized. Lastly, for each modality of the signal, time domain, frequency domain, and statistical features were extracted (mean, standard deviation and power spectral density for motion; inter-beat interval statistics and LF/HF ratio for

HRV). Multi-modal fusion of feature-level representations was done by means of both early fusion (concatenation) and late fusion (decision level ensemble).

Model Evaluation

The use of standard metrics for performance evaluation, including Accuracy, Precision, Recall, F1-Score and Confusion Matrices were used to evaluate Activity Recognition Performance. Mean Absolute Error and Spearman Correlation were used to evaluate Continuous Fatigue/Stress Estimation Performance. Generalization of results was evaluated through leave-one-subject-out testing. Statistical significance of the findings was assessed by conducting paired t-tests and McNamar's test ($p < 0.05$).

Feasibility and Usability Assessment

Using a mixed methods approach, 50 participants completed the System Usability Scale (SUS) and participated in semi-structured interviews that focused on assessing comfort with the device, cultural acceptability, and their willingness to use it over an extended period within Pakistan. The methodology used in this study considered the challenges faced by users in resource-limited areas, such as interruptions in internet connectivity and differences in activity patterns due to local customs and climate conditions, while providing sufficient ecological validity. All data collected in this study were anonymized and securely stored in accordance with ethical standards.

Table 1 Demographic Information of Participants (N = 120)

Characteristic	**n (%) M ± SD**
Age (years)	35.4 ± 12.6
Gender	
Male	68 (56.7%)
Female	52 (43.3%)
Province	
Punjab	72 (60.0%)
Sindh	48 (40.0%)
Health Status	
Healthy	60 (50.0%)
Reporting chronic fatigue/stress	40 (33.3%)
Diagnosed chronic conditions (hypertension, post-COVID fatigue)	20 (16.7%)

Demographic information on the 120 subjects is shown in Table 1. The mean age was 35.4 (SD = 12.6), indicating considerable variability. In terms of gender, participants were comprised of 68 men (56.7%) and 52 women (43.3%). A large percentage of the sample resided in Punjab (60.0%) while 40.0% of subjects lived in Sindh. Of the health status, half (50.0%) of respondents described themselves as generally healthy, 33.3% described having fatigue or chronic stress, and 16.7% had been diagnosed with a chronic illness such as hypertension or post-COVID fatigue.

Table 2 Collected Data Set

Phase	**Participants**	**Duration per Participant**	**Total Recording Hours**	**Key Signals Collected**	**Conditions Covered**
Controlled	80	2–3 hours	220	HR, HRV (PPG-derived), motion (accelerometer/gyroscope)	Standardized activities, induced stress (Trier Social Stress Test), induced fatigue

					(prolonged tasks)
Real-world free-living	120	7–10 days	8,500	HR, HRV, motion	Normal daily routines (e.g., walking, sitting, commuting in urban/semi-urban settings)
Total	**120**	-	**8,720**	Multi-modal time-series	Diverse cultural/environmental contexts (e.g., heat, daily prayers, traffic)

Table 2 provides an overview of the dataset obtained from both phases of the study. In the first part of the study, controlled observations took place using 80 participants, each monitored for 2–3 hours per day; this provided a total of 220 hours' worth of collected data. Heart rate (HR), heart rate variability (HRV), and motion data from accelerometer/gyroscope sensors were recorded while subjects experienced different activities and experiences which had been purposely created to induce stress (using TSS) and fatigue (using longer tasks). In the second phase of the study, a free-living observation study where participants were able to use the facility, data was collected from all 120 participants for several days (7–10 days), inclusive of 8,500 hours of collected data. During these observations, heart rates and heart rate variabilities were captured for normal daily activities such as walking, sitting, commuting through urban and suburban areas. All together these two phases resulted in 8,720 hours of multimodal time series data encompassing a variety of environmental and cultural influences such as heat, prayer, and transportation-related behaviors.

Table 3 Preprocessing and Fusion Outcomes

Step	**Technique Applied**	**Impact on Data Quality**
Noise filtering	Butterworth low-pass filter	Reduced signal noise by 78%
Artifact removal	Adaptive filtering for PPG motion artifacts	Improved HRV validity in 92% of segments
Segmentation	10-second windows, 50% overlap	Yielded 512,340 usable windows
Individual variability adjustment	Z-score normalization per participant	Accounted for baseline differences (e.g., higher resting HR in hot climates)
Multi-modal fusion	Early fusion (feature concatenation) + late fusion (ensemble)	Enhanced feature robustness; reduced variability from cultural factors (e.g., prayer movements) by 65%

Table 3 depicts the signal processing and subsequent integration performed on the collected data. By utilizing a Butterworth low-pass filter as a noise-reduction mechanism, 78% reduction in noise is expected through application of the filter to the original signals. The additional motion contamination from PPG data has been minimized via using adaptive noise filtering techniques, allowing valid HRV estimation on a total of 92% of the analyzed data frames. The resultant cleaned signals were organized into a 10s windowed format with a 50% overlap for the analysis. A total of 512,340 window segments were identified for potential use in this study. Participant level Z-score normalization was applied to control for individual variability and different baseline resting HRs associated with environmental stresses such as heat. A combination of early fusion methods via concatenating features from multiple data segments and late fusion via using ensembles has enhanced the ability of the features to be robust by decreasing the amount of variability caused by cultural factors (i.e. prayer) by 65%.

Table 4 Performance Metrics for Activity Recognition and State Detection (10-Fold Cross Validation)

Task	Model (Multi-Modal Fusion)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Human Activity Recognition (e.g., walking, sitting, stairs)	Hybrid CNN-LSTM	94.8	95.2	94.5	94.8
Stress Detection (binary: stressed vs. baseline)	State-aware ensemble	91.2	90.8	91.5	91.1
Fatigue Detection (binary: fatigued vs. non-fatigued)	State-aware ensemble	89.7	89.4	90.1	89.7
Chronic Indicators (e.g., abnormal HRV patterns correlated with hypertension/post-fatigue)	Multi-task learning	87.5	88.0	87.2	87.6

Table 4 reports the performance metrics of the proposed models for activity recognition and physiological state detection using 10-fold cross-validation. The hybrid CNN–LSTM model achieved high performance in human activity recognition tasks, such as walking, sitting, and stair usage, with an accuracy of 94.8% and an F1-score of 94.8%. For stress detection, the state-aware ensemble model demonstrated strong classification capability, achieving an accuracy of 91.2%, with balanced precision and recall values of 90.8% and 91.5%, respectively. Similarly, fatigue detection using the same state-aware ensemble model yielded an accuracy and F1-score of 89.7%, indicating reliable discrimination between fatigued and non-fatigued states. For identifying chronic indicators, including abnormal HRV patterns associated with conditions such as hypertension and post-fatigue, the multi-task learning approach achieved an accuracy of 87.5% and an F1-score of 87.6%, reflecting robust performance across more complex and long-term physiological patterns.

Table 5 System Useability Scale and Qualitative Feedback (n=50)

Metric	Score/Response	Interpretation
SUS Score (mean)	82.4 ± 8.6	"Excellent" (above 80)
Comfort during wear	92% rated "comfortable/very comfortable"	Suitable for extended use
Cultural appropriateness	88% agreed "fits daily life/routines"	No interference with clothing/practices
Willingness for long-term use	85% "likely/very likely"	High feasibility in low-resource settings
Common feedback	Positive: Affordable devices, easy app; Suggestions: Better heat resistance	Supports public health integration

The System Usability Scale (SUS) Summary of qualitative Feedback from Fifty Participants is in Table 5. The average SUS score was 82.4 ±8.6 out of 100, indicating an "Excellent" Usability rating, which means that users have an overall high Howard satisfaction with the system. Most participants (92%) rated the system as being comfortable or very comfortable to wear over long periods of time. Of the 88% who stated that the device fits in well with their lifestyle and daily routines, none of them indicated that there were any barriers created due to difficulties in wearing or taking off traditional clothing during normal day-to-day activities. Of the 85% of participants, they expressed the likelihood or strong willingness to use the system over the long term, indicating high feasibility to use the system in low-resource settings. Most participants provided positive feedback about the affordability of the devices used and the ease of use of the mobile application associated with the device. Participants offered suggestions to improve the heat resistance of the device to provide the device with a greater chance for public health integration.

Discussion

This study has tested and developed a state-aware human activity recognition (HAR) system that's able to collect multi-modal physiological and motion data from off-the-shelf wearable devices to monitor fatigue, stress and early signs of chronic disease among a population in Pakistan. The results show that these types of systems can perform very well in a resource-limited setting, thereby filling an important gap in the current HAR literature, which has focused almost entirely on controlled environments and Western populations.

The collection of over than 8720 hours of multi-modal data from 120 participants during both controlled and free-living conditions (Objective 1) represents a key contribution to research. This dataset contains some of the first datasets around the world recording physiological and motion signals of individuals living in Pakistan's environmental and social/cultural context, such as cultural movements (e.g. prayer movements) and the cultural practice of travelling in traffic, as well as capturing the effects of environmental challenges such as heat and humidity. In comparison to the majority of the previously collected datasets that are designed to collect physiological data in a laboratory setting and/or were developed based on participants' lifestyles within the Western world (Chatzaki and Tsiknakis, 2025; Hongn et al., 2025), the data set presented here also captures the daily routine and stressors of people living in lower/middle-income countries, thereby increasing the ecological validity of the data.

The challenges of the presence of artifacts caused by motion, physiological variability among individuals, and environmental noise were addressed through effective preprocessing and multimodal fusion (Objective 2). There was a significant decrease in the amount of noise (78%) and an increase in the validity of the signal. These results are consistent with current best practices in wearable-based monitoring (Adão Martins et al., 2021; Kakhi et al., 2025). Adaptive filtering and normalization based on the individual participant demonstrated to be most effective in accounting for high baseline heart rates that are typically associated with hot climate environments and culturally specific body positions. Therefore, effective preprocessing in accordance with cultural contexts is critical to ensuring accurate results from wearable devices when examined outside of traditional Western settings.

The results from this research show that using multi-modal fusion of Biometric Sensor Data (e.g. Heart Rate Variability [HRV]) with Motion/Activity Data lead to significant and improved sensitivity and specificity when assessing such states as activities, stress, fatigue, and chronic conditions across subjects of the same demographic (Pakistani) (Iqbal et al., 2025) as opposed to using each of the respective HRV and Motion/Activity Data sources separately (Lazarou & Exarchos, 2024; Yang et al., 2025). Such improvement is critical and indicates significant value to the Integration of Physiological Signals with Motion Data to achieve nuanced state awareness in Activity Recognition. Furthermore, these results indicate excellent subject-independent performance, suggesting ability to generalize well across groups differing by Age, Gender and Health Status for the Pakistani Cohort and hence highlight the potential utility of this Framework for early detection of chronic conditions such as hypertension-related HRV disturbances or persistence of Fatigue due to COVID-19 (Qadir et al., 2024).

Assessed for usability and cultural acceptability (O4) yielded excellent rates of acceptance (82.4 mean SUS score) and a high probability of continued use. Participants expressed a preference for using Garmin Vivosmart 5 and Fitbit Charge 6 devices because of their non-intrusive nature, ease of purchase in Pakistan, and ability to work with most Android smartphones. Qualitative comments indicated minimal interference with daily cultural practices (e.g., performing wudu, praying) or attire, thus overcoming one of the largest barriers to adoption in conservative cultures. The results support the viability of incorporating these types of systems into Pakistan's public health framework, particularly as they relate to community-based management of NCDs and the mental health burden.

Limitations of Study

A few limitations must be addressed, even with the strengths. Even though the sample for this study was diverse, it was taken from urban and semi-urban areas within Punjab and Sindh, which could limit the ability to generalize the results to any other region of Pakistan, particularly those in rural areas. Additionally, since the study measured HRV using PPG, rather than using ECG, it may have underestimated the accuracy of the results when participants were in high-motion activities. Future research will need to include more participants from throughout the country of Pakistan as well as include longer-term follow up assessments of health-related issues to show how HRV can predict the progression of chronic disease.

Conclusion

Based on this research, it can be concluded that there is support for using accessible wearable technology to create a multi-modal state aware approach to Human Activity Recognition (HAR). This approach is (1) accurate, (2) achievable and culturally appropriate and (3) effectively addresses the challenges related to fatigue, stress and chronic diseases within the Pakistani population. The framework represents a low-cost scalable means of addressing the increasing prevalence of Cancers; Cardiovascular Diseases and Mental Health problems in Low-Resource Environments in Pakistan. Future work should include evaluating the feasibility of using only smartphones for the implementation of the multi-modal state aware HAR framework to create a barrier-free solution. Integrating with National Health Information Systems would allow for immediate recognition and response to at-risk individuals.

REFERENCES

Adão Martins, N. R., Annaheim, S., Spengler, C. M., & Rossi, R. M. (2021). Fatigue monitoring through wearables: A state-of-the-art review. *Frontiers in Physiology*, *12*, Article 790292. https://doi.org/10.3389/fphys.2021.790292

Chatzaki, C., & Tsiknakis, M. (2025). An overview of stress analysis based on physiological signals: Systematic review of open datasets and current trends. *Sensors*, *25*(23), 7108. https://doi.org/10.3390/s25237108

Fang, S., & Mushtaque, I. (2024). The Moderating Role of Health Literacy and Health Promoting Behavior in the Relationship Among Health Anxiety, Emotional Regulation, and Cyberchondria. *Psychology Research and Behavior Management*, *Volume 17*, 51–62. https://doi.org/10.2147/prbm.s446448

Govindasamy, V., Khan, M. N., Awan, Z. K., Wandala, A., Akbar, M. B., Kamran, A., Attian, M., Shahbaz, W., Mahmood, A., Al Shamsi, M., & Ameer, Z.-e.-R. F. (2025). Association between perceived stress and fatigue severity in patients with chronic illnesses. *Cureus*, *17*(6), Article e86444. https://doi.org/10.7759/cureus.86444

Hongn, A., Bosch, F., Prado, L. E., Ferrández, J. M., & Bonomini, M. P. (2025). Wearable physiological signals under acute stress and exercise conditions. *Scientific Data*, *12*, Article 520. https://doi.org/10.1038/s41597-025-04845-9

Hosseini, M., Sohrab, F., Gottumukkala, R., Bhupatiraju, R. T., Katragadda, S., Raitoharju, J., Iosifidis, A., & Gabbouj, M. (2025). A multimodal stress detection dataset with facial expressions and physiological signals. *Scientific Data*, *12*, Article 1844. https://doi.org/10.1038/s41597-025-05812-0

Iqbal, R., Qureshi, A., Jaffar, R., Wajiha Omair, Imam, A. A., & Khan, U. I. (2025). Cardiometabolic multimorbidity and symptoms of common mental disorders in a primary healthcare system for low-income urban population in Pakistan. *PLOS Global Public Health*, *5*(9), e0005140–e0005140. https://doi.org/10.1371/journal.pgph.0005140

Jaleel, H., Arshad, M., Iqbal, S. P., Imran, Z., Azhar, Z., Ahmad, M., Amjad, M., Aamer, M., & Ghafoor, F. (2022). Fatigue, anxiety and depression due to the challenges faced by patients undergoing hemodialysis and their caregivers during Covid-19 pandemic. *Medical Research Archives*, *10*(9). https://doi.org/10.18103/mra.v10i9.3058

Kakhi, K., Jagatheesaperumal, S. K., Khosravi, A., Alizadehsani, R., & Acharya, U. R. (2025). Fatigue monitoring using wearables and AI: Trends, challenges, and future opportunities. *Computers in Biology and Medicine*, *195*(Suppl C), Article 110461. https://doi.org/10.1016/j.compbiomed.2025.110461

Lazarou, E., & Exarchos, T. P. (2024). Predicting stress levels using physiological data: Real-time stress prediction models utilizing wearable devices. *AIMS Neurosciences*, *11*(2), 76–102. https://doi.org/10.3934/Neuroscience.2024006

Qadir, S., Khan, N. S., Anjum, G., & Uddin, N. (2024). A wearable sensors dataset for stress & boredom associated activity recognition. *Data in Brief*, *54*, 110550. https://doi.org/10.1016/j.dib.2024.110550

Raza, T., Chaudhry, M. A., Masud, A., Ahmed, M. G., Ahmed, M., & Amin, B. (2020). Mental health and chronic fatigue syndrome: Is mental health the culprit behind your fatigue? *Biomedica*, *36*(2), 183–187.

Sansakorn, P., Mushtaque, I., Muhammad Awais-E-Yazdan, & Muhammad. (2024). The Relationship between Cyberchondria and Health Anxiety and the Moderating Role of Health Literacy among the Pakistani Public. *International Journal of Environmental Research and Public Health*, *21*(9), 1168–1168. https://doi.org/10.3390/ijerph21091168

Schreiber, P., & Maleshkova, M. (2025). VitaStress: A multimodal dataset for stress detection. In *Proceedings of the 27th International Conference on Multimodal Interaction* (pp. 673–681). https://doi.org/10.1145/3716553.3754337

Shahzadi, K., Shahid, H., Malik, M., Raza Khan, H., Talha, M., & Nazir, P. (2023). Prevalence of chronic fatigue in post COVID-19 patients in twin cities. *Pakistan Journal of Health Sciences*, *4*(06), 77–81. https://doi.org/10.54393/pjhs.v4i06.839

Yang, S., Gao, Y., Zhu, Y., Zhang, L., Xie, Q., Lu, X., Wang, F., & Zhang, Z. (2025). A deep learning approach to stress recognition through multimodal physiological signal image transformation. *Scientific Reports*, *15*(1), Article 22258. https://doi.org/10.1038/s41598-025-01228-3