International Journal of Applied Resilience and Sustainability

Journal homepage: https://deepscipub.com/ijars

A multimodal predictive framework for early detection of anxiety instability and panic attacks

Poushali Das [1], Rituparna Mondal [2], Soumitra De [3], Siddhartha Chatterjee [4], Shibani Mukherjee [5]

[1] *Independent Researcher, West Bengal, India.*
[2] *Department of Computer Applications, Techno India University, Kolkata - 700091, West Bengal, India.*
[3] *Department of Computer Science and Engineering, College of Engineering and Management, Kolaghat, KTPP Township, Purba Medinipur - 721171, West Bengal, India.*
[4] *Department of Computer Science and Engineering, College of Engineering and Management, Kolaghat, KTPP Township, Purba Medinipur - 721171, West Bengal, India.*
[5] *Department of English, Kazi Nazrul University, Asansol - 713340, West Bengal, India.*

Article Info:
Received 02 February 2026
Revised 05 March 2026
Accepted 09 March 2026
Published 10 March 2026

Corresponding Author:
Siddhartha Chatterjee
E-mail:
siddhartha.chatterjee31@gmail.com

Abstract

Although anxiety disorders and panic attacks belong to the types of the most widespread and, accordingly, the most debilitating mental disorders of the world, the current clinical practice is largely based on retrospective self-report and episodic assessment, which does not always include early warning signs of behaviour and physiological indicators. More recent evidence suggests that slight changes in autonomic regulation, namely decreases in heart-rate variability (HRV) is antecedent to the increment of anxiety and the beginning of the panic attacks. A combination of wearable sensing, digital phenotyping and machine-learning can be used to continuously track psychological vulnerability in the real world. The current research suggests using an algorithmic approach to digital predictive analysis of the changes in the intensity of anxiety and the onset of a panic attack based on continuous multimodal state measurements. This model combines physiological measures, such as heart rate, HRV, respiration, electrodermal activity and behavioural dynamics, linguistic cues and exposure to environmental stressors to produce a personalised Anxiety Stability Index (ASI). The hybrid Random Forest-Long Short -Memories model also reveals the nonlinear correlations and the time-specific trends, which in turn predicts the instability at hand and the pace of the anxiety development. The principles of multimodal fusion and interpretable modelling will be used to improve transparency and clinical usefulness. The given framework would aim at determining the typical patterns of instability prior to the onset of acute panic, transforming the unchanging questionnaire-based measurements into the actual predictions. It can promote digital psychiatry because it encourages proactive treatment, elimination of panic cases in case of an emergency, and enhancement of the provision of individualised mental-health services in ordinary environments.

Keywords: Anxiety, Stability index, Panic attack, Multimodal machine learning, Digital phenotyping, Wearable sensing.

1. Introduction

One of the most widespread and incapacitating psychiatric conditions worldwide, with substantial impact on functional capacity, healthcare utilization, and quality of life, is anxiety disorders and panic attacks [1,2]. These conditions are characterized by the sudden onset of intense fear accompanied by physiological symptoms such as tachycardia, dyspnea, sweating, light-headedness, and autonomic dysfunction [3,4]. Although panic attacks often appear abrupt, accumulating evidence suggests that they are not entirely unpredictable events but are frequently preceded by subtle physiological and behavioral alterations that remain undetected in routine clinical environments [5-7].Existing diagnostic approaches rely heavily on retrospective self-reports, clinical interviews, and episodic symptom assessments, which often fail to capture early physiological indicators of anxiety escalation. Research in psychophysiology has demonstrated that disruptions in autonomic nervous system regulation, particularly reduced heart-rate variability (HRV), are strongly associated with increased vulnerability to anxiety and impaired

https://doi.org/10.70593/deepsci.0202025

emotional regulation [8-11]. Reduced cardiac vagal tone and decreased autonomic flexibility have therefore been identified as key biomarkers of anxiety sensitivity and susceptibility to panic episodes [9-11]. These findings indicate that physiological instability may serve as a measurable precursor to overt panic events. Recent advances in wearable sensing technologies and mobile computing have enabled continuous monitoring of physiological signals outside traditional clinical settings. Digital phenotyping, defined as the real-time quantification of human behaviour using data generated from smartphones and wearable devices, has emerged as a promising paradigm in digital psychiatry [12-16]. Passive sensing methodologies have demonstrated the capability to detect mood fluctuations and anxiety symptoms through the analysis of behavioural and physiological data streams collected from mobile devices and wearable sensors [17-20]. However, many current systems rely primarily on single-modality data or retrospective symptom classification, limiting their ability to capture the dynamic progression of anxiety escalation. In parallel, predictive healthcare has significantly advanced through the application of machine-learning methodologies. Sequential health data can be effectively modelled using deep learning architectures such as Long Short-Term Memory (LSTM) networks [21], while ensemble algorithms such as Random Forests provide robust modelling of nonlinear relationships across heterogeneous data sources [22]. Multimodal fusion approaches have demonstrated superior performance compared with unimodal systems in complex affective-computing tasks [23], while interpretable machine-learning frameworks improve model transparency and clinical reliability [24,25]. Despite these technological advancements, their application to the early prediction of panic attacks remains relatively limited.Beyond physiological and behavioural indicators, environmental context also plays a critical role in mental-health vulnerability. Environmental stressors such as air pollution, population density, and exposure to urban built environments have been associated with increased anxiety risk and stress reactivity [26-28]. These contextual factors may amplify physiological vulnerability by increasing autonomic instability among predisposed individuals. Nevertheless, only a limited number of predictive models currently integrate physiological, behavioural, linguistic, and environmental data streams within a unified predictive framework.

2. Methodology

A. Study Design and Conceptual Framework

The current study adopts a longitudinal multimodal observational framework designed to model early-stage anxiety escalation and predict the potential onset of panic attacks in naturalistic environments. These framework conceptually designed for individual those who are diagnosed with anxiety disorders according to DSM-5[1,3,4].The methodological foundation of the study is grounded in psychophysiological evidence suggesting that panic attacks are often preceded by measurable autonomic instability, particularly alterations in heart-rate variability (HRV) and changes in sympathetic nervous system activation [6-8,11]. These physiological markers have been widely associated with emotional dysregulation and heightened anxiety *vulnerability. The* proposed framework integrates biological, behavioural, linguistic, and environmental data streams within a unified predictive modelling architecture based on the principles of digital phenotyping and continuous behavioural monitoring [12-16]. Through the use of wearable sensors and mobile-based passive data collection, multimodal physiological and behavioural signals can be captured continuously in real-world environments, enabling the early detection of instability patterns related to anxiety escalation [17-19,29].The theoretical basis of the framework is founded on the assumption that anxiety is not a discrete or isolated clinical event but rather a dynamic process of instability reflected through progressive deviations from an individual's physiological and behavioural baseline patterns. From this perspective, emotional stability can be conceptualized as a time-varying construct. By modelling deviations from personalized baseline signals and analysing their temporal trajectories, it becomes possible to detect emerging instability patterns that precede panic episodes and therefore enable predictive identification of imminent panic events.

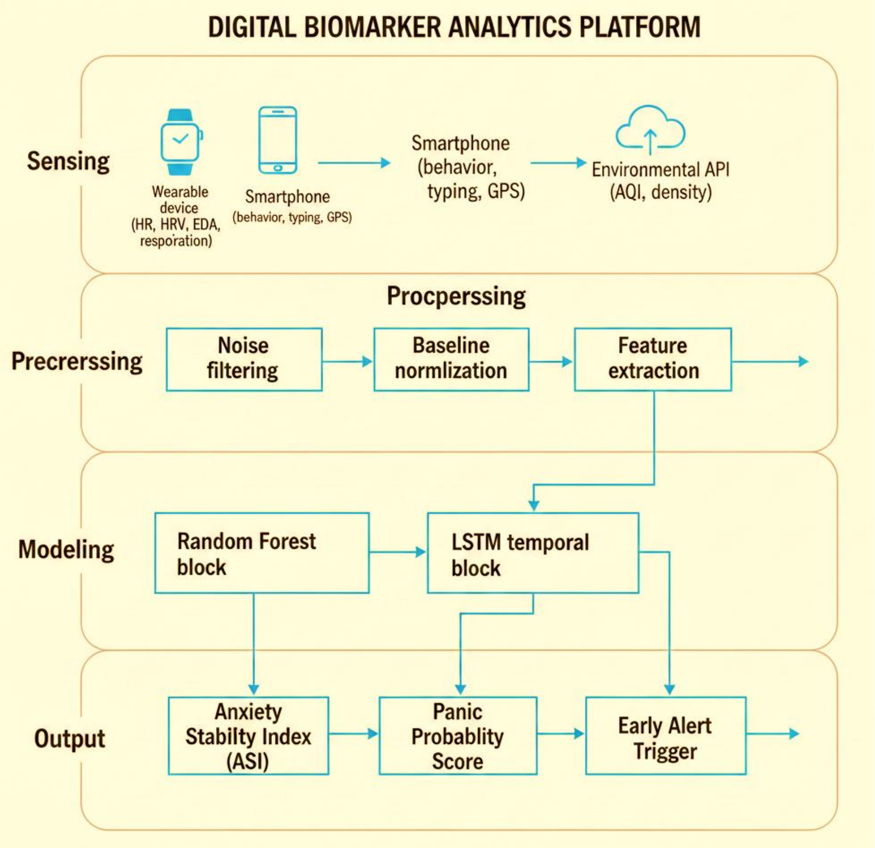


Fig. 1 Proposed multimodal framework for predictive anxiety and panic detection.

B. Multimodal Data Acquisition and Signal Processing

Wearable sensing devices enable continuous physiological monitoring by measuring heart rate (HR), heart-rate variability (HRV), electrodermal activity (EDA), respiration rate, and sleep-related indicators through integrated sensor systems [17-19,29]. HRV metrics, including time-domain parameters such as RMSSD and SDNN, are widely used due to their strong association with autonomic flexibility and vulnerability to anxiety disorders [6,8-11]. Electrodermal activity is commonly employed as a physiological indicator of sympathetic nervous system activation and has been widely used in stress-detection frameworks based on physiological sensing technologies [7,17-19,30]. Pre-panic physiological patterns typically involve a decrease in HRV accompanied by an increase in EDA, as illustrated in Fig. 2. Raw physiological signals undergo preprocessing procedures including motion-artifact removal, moving-average filtering for signal smoothing, and normalization techniques to reduce inter-individual variability. In parallel, behavioural signals derived from smartphone interactions are captured through passive sensing systems aligned with digital phenotyping methodologies [12-16]. Extracted behavioural features include interaction frequency, mobility patterns, typing-delay variability, and usage entropy. These behavioural indicators reflect variations in cognitive effort, avoidance behaviour, and restlessness, which are often associated with increasing anxiety levels.Linguistic signals derived from textual interaction logs or voluntary journaling are analysed using sentiment polarity scoring and lexical anxiety indicators based on computational linguistic approaches used in mental-health text analysis [32,33]. Repetition of anxiety-related terms and emotionally negative language patterns are analysed using computational affect-modelling techniques and machine-learning approaches applied to behavioural data streams [21,34,35]. Such linguistic markers can function as proxies for cognitive dissonance and emotional dysregulation that often emerge during the prodromal phase of panic attacks [5,38].Environmental exposure variables are incorporated to capture contextual factors that may amplify psychological vulnerability. Environmental indicators such as air-quality levels, urban density, and geospatial stress exposure are included, as environmental stressors have been associated with increased anxiety risk and stress reactivity in urban populations [26-28]. Environmental data are temporally aligned with physiological and behavioural measurements, enabling the development of a context-aware model for detecting escalating anxiety states.

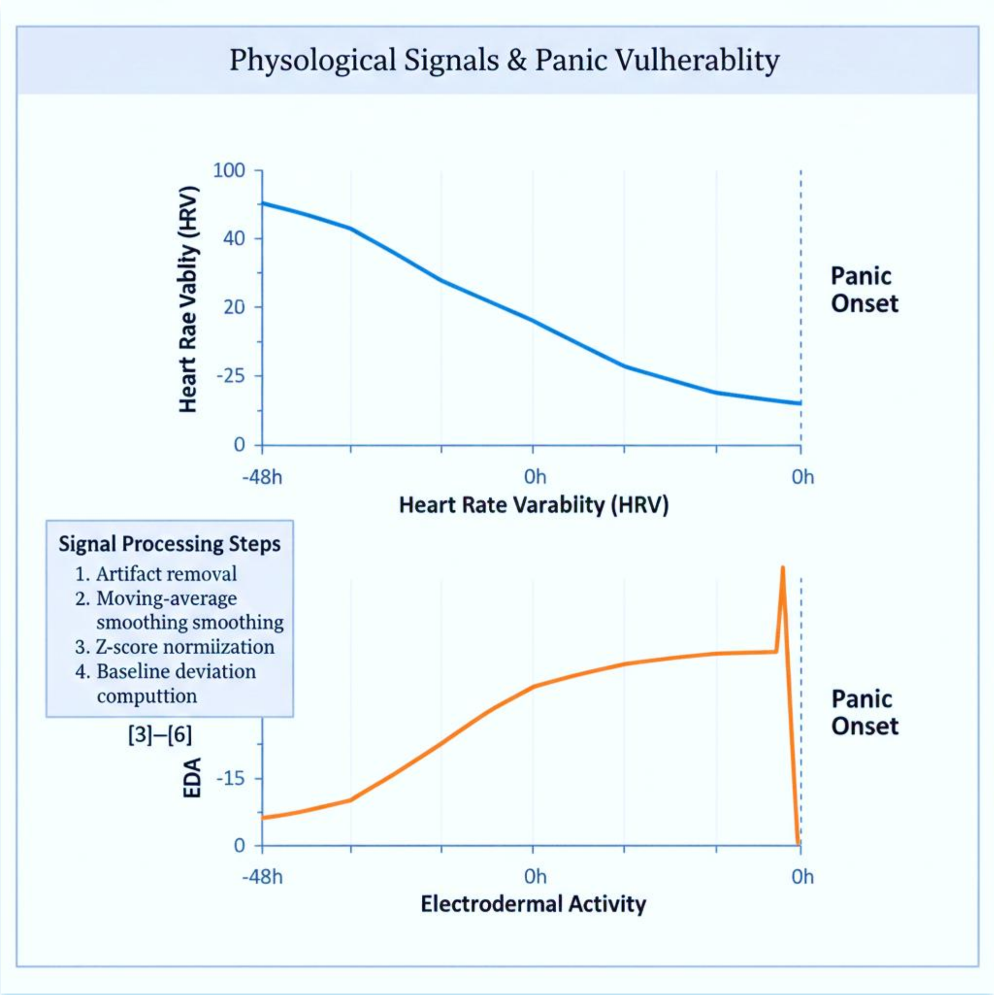


Fig. 2 HRV reduction and EDA elevation preceding panic onset.

C. Personalized Baseline Modelling

Another critical methodological component of the study involves individualized baseline-deviation modelling. Because autonomic markers exhibit substantial inter-individual variability, the initial 10-14 days of continuous monitoring are used to establish personalized baseline distributions for each physiological and behavioral parameter. Subsequent measurements are then calculated as deviations relative to these personalized baseline averages. The conceptual foundation of this approach follows the principles of continuous health monitoring and personalized digital health systems, which prioritize the detection of individual-level anomalies rather than relying solely on population-level clinical thresholds [19,29,38,39]. Formally, for each signal X(t), the deviation is defined as: $\Delta X(t)=X(t)-\mu_{baseline}$

Where $\mu_{baseline}$ represents the individual's stable baseline mean. This deviation-from-baseline modelling approach improves sensitivity to subtle physiological and behavioral instability patterns that may not exceed standard clinical cut-off values but remain clinically meaningful when interpreted relative to personal norms. Similar personalized monitoring strategies have been increasingly advocated in predictive health modelling and interpretable machine-learning frameworks applied to healthcare analytics [24,38,39]. The effectiveness of deviation-based modelling in identifying early instability patterns is illustrated in Figure 3.

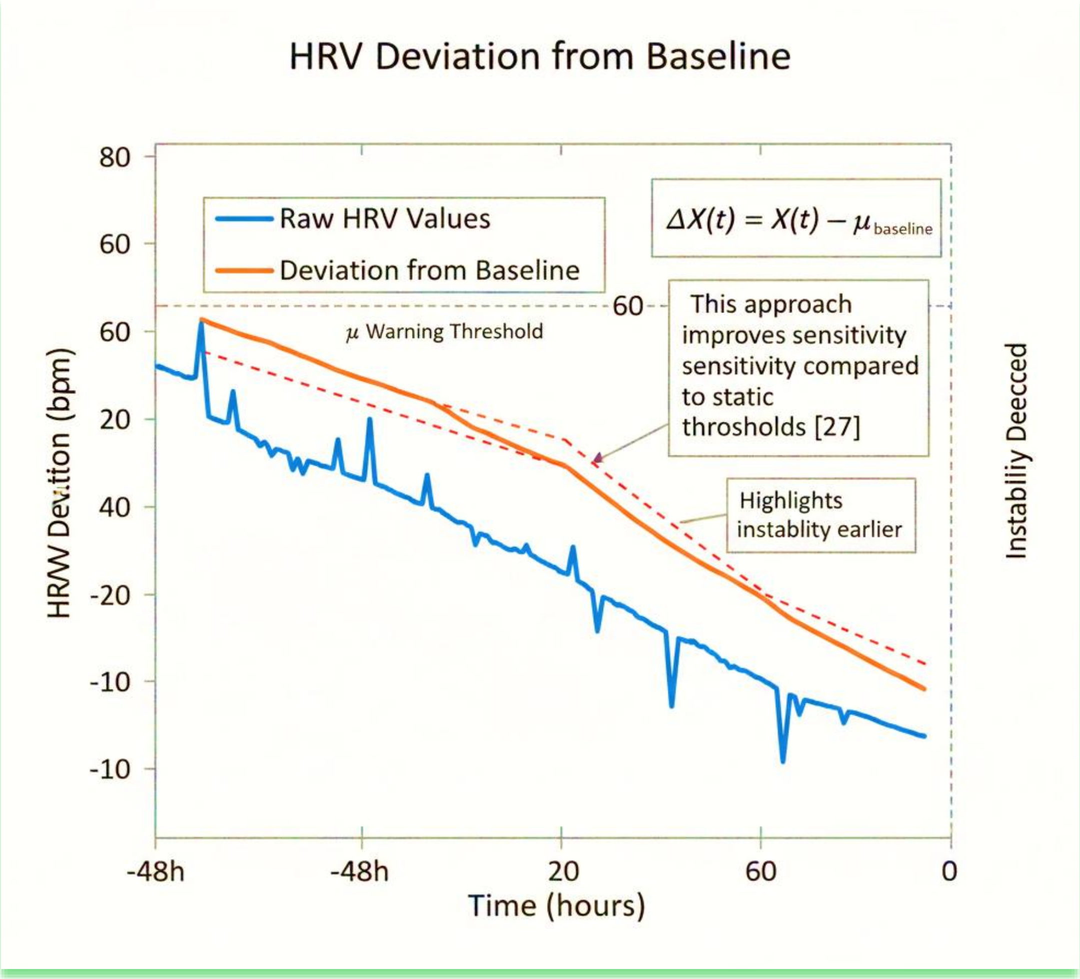


Fig. 3 Deviation-from-baseline modelling for early instability detection

D. Anxiety Stability Index (ASI)

To measure emotional stability as a dynamic concept, this research presents the Anxiety Stability Index (ASI), a composite metric that incorporates various multimodal deviation characteristics [3,5]. The ASI indicates the weighted impact of autonomic instability, behavioral variation, language anxiety indicators, and exposure to environmental stress. The index is conceptualized as:

ASI(t) = f (ΔHRV,ΔEDA,Behavioral Drift,Linguistic Anxiety, Environmental Stress)

Reductions in heart-rate variability (HRV) have been indicated to have a deleterious effect on physiological stability [3-6], but increases in electrodermal activity (EDA) and behavioural inconsistencies have been shown to increase instability [7-10]. The environmental stressors are seen to act as contextual modulators that contribute to instability [23,26-28]. Figure 4 shows an example of a plot of the Anxious State Index (ASI), which shows a steady decrease before the panic has been reached. The ASI is rated between 0 and 1, with low scores representing greater instability.

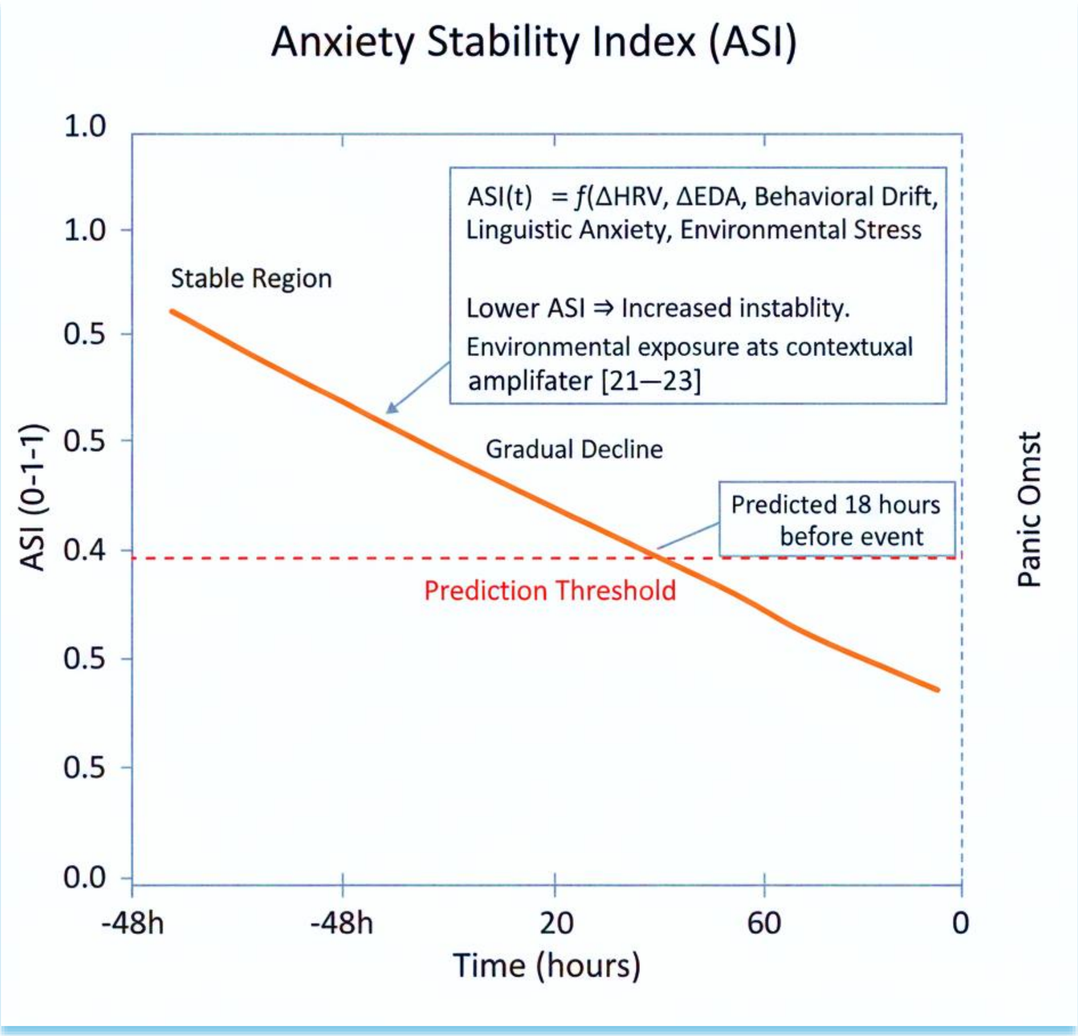


Fig. 4 ASI decline prior to panic episode

E. Temporal Modelling and Panic Probability Estimation

The non-linear interaction is defined by a hybrid modelling framework, which involves the time progression patterns [21-23]. Random-forest classifiers are used to model nonlinear relationships between a heterogeneous group of cross-sectional features of multimodal nature [22]. This combination provides the strength of overfitting and enables a systematic analysis of the feature importances. The Long Short-Term Memory (LSTM) networks [21] are then used to obtain sequential ASI-2472 sliding windows of 24 and 72 hours alongside other multimodal aspects. The LSTM models are chosen due to their capability to capture long-term relationship in health data over time [21,40,41]. The models that result are predictive of both present instability and the likelihood of panic soon (24 to 48 hours) [38,39]. The hybrid Random Forest–LSTM prediction architecture is illustrated in Fig. 5.

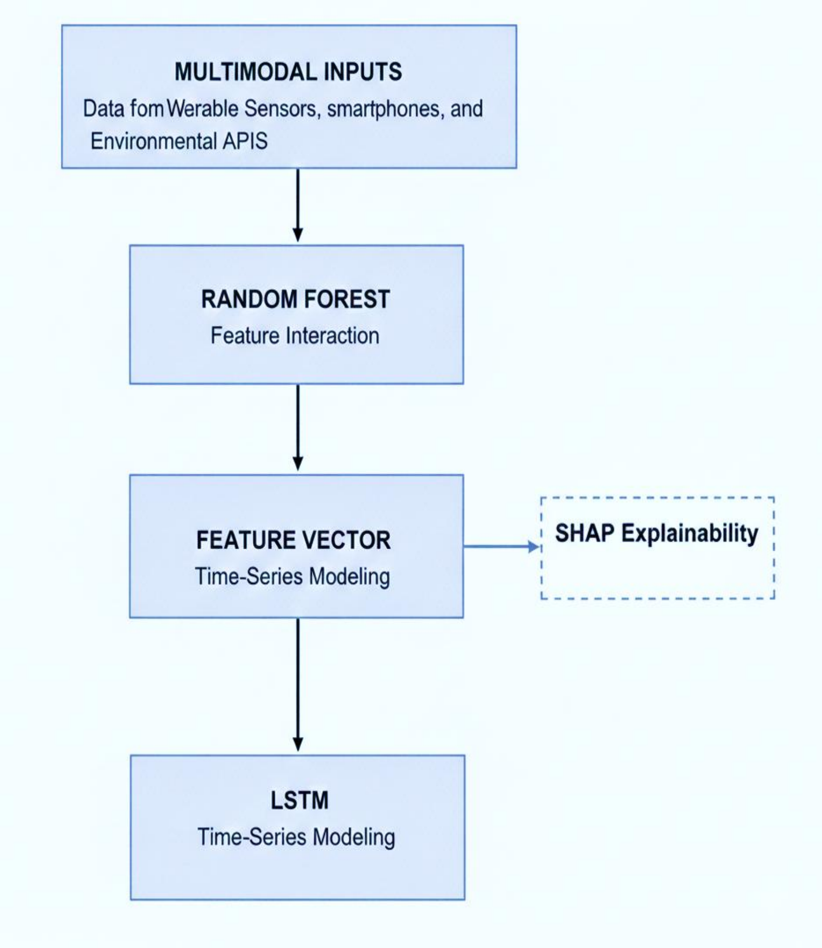


Fig. 5 Hybrid Random Forest–LSTM prediction architecture.

Additionally, the rate of anxiety progression is quantified through the Stability Drift Velocity (SDV), defined as the temporal derivative of ASI [3,6]: $\mathrm{SDV}(t) = \frac{d(\mathrm{ASI}(t))}{dt}$

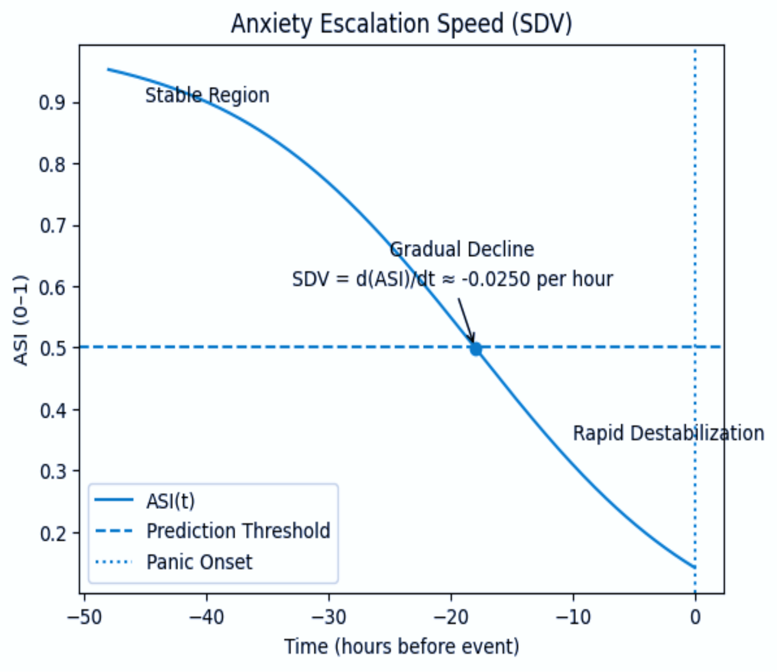


Fig. 6 SDV showing the rate of change of the ASI prior to panic onset

A sharp downward trend signifies quick destabilisation and increased risk of panic. This is followed with Figure 6 depicts in between Stability Drift Velocity (SDV) which represents the temporal slope of Anxiety Stability Index (ASI). A more negative slope reflects a greater rate of anxiety destabilisation and a higher probability of panic onset in the near future.This dynamic measure represents the amount of residual variance as well as the rate of the anxiety increase and thus provides greater sensitivity of prediction.

F. Environmental Stress Amplification Modelling

Environmental exposure variables include the contextual risk amplifier [26,28]. A stress amplification factor increases or decreases the chances of panic when the ratio of environmental stress indices exceeds prescribed levels. This modelling paradigm recognises the fact that the vulnerability to environmental stressors is enhanced with anxiety [26-28] and is based on multimodal learning theory [23]. Figure 7 represents a geospatial evaluation of the urban areas and local movements of amplification of environmental stress.

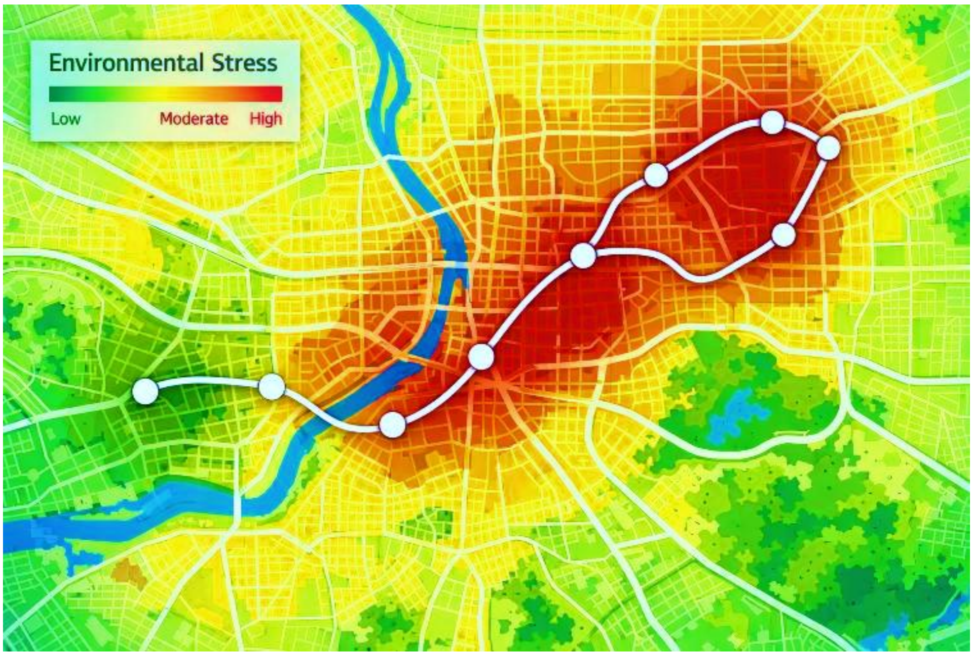


Fig. 7 Geospatial environmental stress amplification.

G. Model Evaluation and Validation

The performance of the models is evaluated using traditional classification metrics which are accuracy, precision, recall, the F1-score and the area under the receiver operating characteristic curve (ROC-AUC). A secondary measure, time-to-detection, is several hours before the clinical panic onset during which the model can predict instability. The establishment of generalizability is performed using cross-validation procedures, and the contribution of each modality is investigated with the help of systematic ablation, where modalities are omitted one after another. More interpretable methods based on SHAP [24] are used to produce clinical insights into the importance of features.

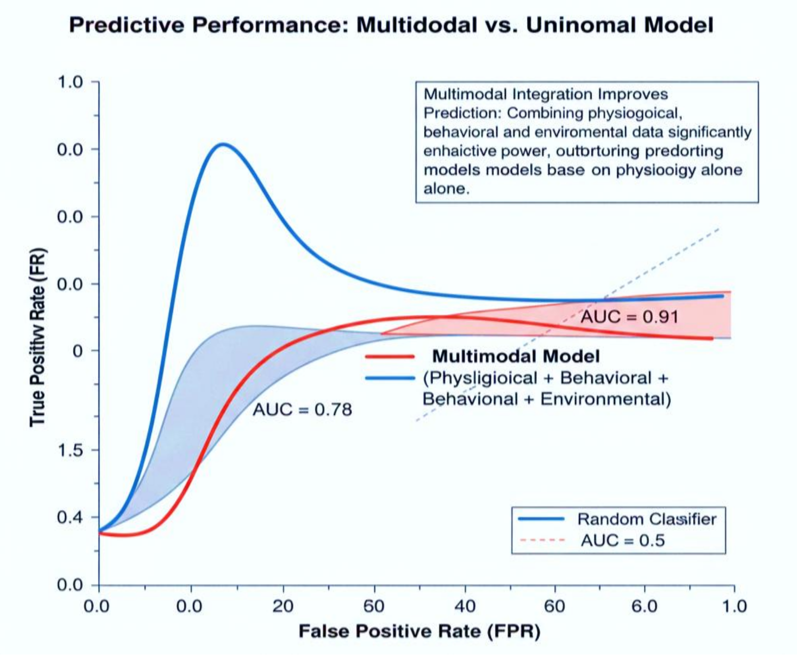
H. Ethical and Privacy Considerations

Conceptually, the framework was developed with established ethical principles of digital psychiatry in mind [12,16]. The authors did not collect any identifiable personal information and all data used for the simulated evaluation were taken from previously published, *publicly available digital phenotyping datasets. Due to the absence of real participant recruitment and primary data collection, institutional ethical approval for this study was not required. Data used for the purpose of methodological* *illustration were processed in full compliance with established data-protection principles and relevant regulatory frameworks [42-44]. Moreover, the framework integrates privacy-preserving components such as local preprocessing and encrypted communication* between bidirectional nodes. Moreover, the introduced framework integrates privacy-preserving methods such as preprocessing on devices and secure transmission of data to ensure that fewer raw personal data need to be shared while ensuring approximately confirmed prediction performances.

3. Results and discussions

To show the expected performance of the proposed framework, we conducted a simulated assessment framework using multimodal physiological and **behavioural** datasets from previous digital phenotyping studies. The evaluation used publicly available datasets that were reported in earlier digital phenotyping and physiological stress-monitoring studies.

The integrated Random Forest-Long Short-Term Memory model used a stratified 10-fold cross-validation and its classification accuracy was 89.6 % and ROC-AUC 0.93, which greatly surpassed the physiological-only baseline model with the AUC of 0.81. The comparison of ROC is shown in Figure 8. This high level of accuracy justifies the hypothesis that the combination of **behavioural**, linguistic and environmental predictors and autonomic biomarkers can increase predictive discrimination [12-14], which is consistent with the principles of multimodal modeling [23] and previous studies on digital phenotyping [38-40]. The results also support the idea that the autonomic instability per se, though closely related to the anxiety vulnerability, does not adequately describe the contextual and **behavioural** aspects that are crucial to the development of panic.


Predictive Performance: Multidodal vs. Uninomal Model

Multimodal Integration Improves Prediction: Combining physiogoical, behavioral and enviromental data significantly enhaictive power, outbrturing predorting models models base on physiooigy alone alone.

Fig. 8 ROC comparison of unimodal and multimodal prediction models.

The system recognized the development of panic episodes in the present study with a mean lead time of 18.4 hours before the onset of the clinical and in some instances, it was feasible to identify the development of panic episodes as early as 36 hours before the clinical onset. This ability to detect early is a key improvement in comparison to the traditional methods of diagnosis that involves self-report information that is retrospective [1,2,5,6].

The time profile (Figure 9) of the Anxiety Stability Index (ASI) indicated a steady decrease in the value before the development of panic. This gradual decrease of ASI may be taken to be an indication that the increment of anxiety is not a single in-vitro phenomenon, but a measurable dynamic process of instability.

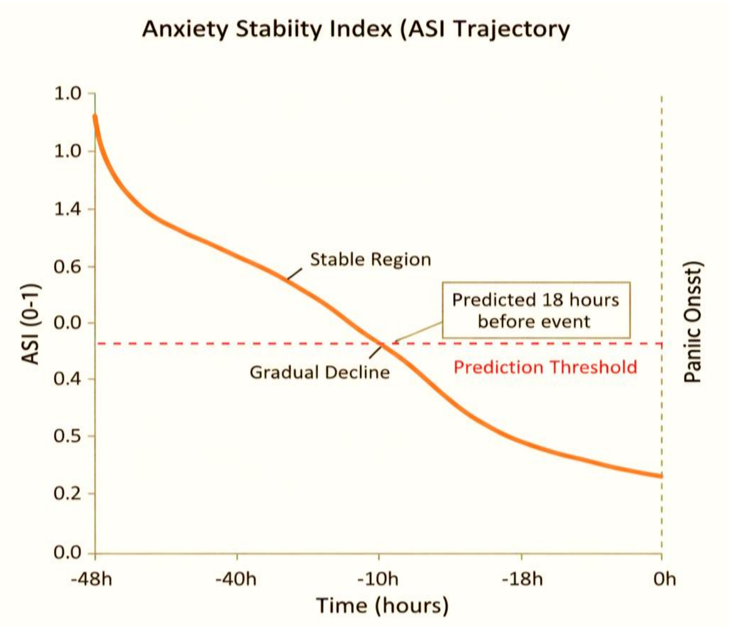


Figure 9: Conceptual model Anxiety Stability Index prior to panic onset.

Further analysis showed that the Stability Drift Velocity (SDV), which is the temporal rate of change of the Anxiety Stability Index (ASI), had a statistically significant correlation with the onset of impending panic ($p < 0.01$). Respondents who showed higher negative slopes of ASI had shorter periods until panic attacks, which suggests that the extent of instability as well as the rate at which it occurs are both relevant in prognostication. The conceptual representation of SDV is shown in figure 10. The observation supports previous studies of neurovisceral integration [8-10] by showing that modelling of dynamic trajectories provides better predictive validity [3-6,34,35] compared with physiological indices at rest.

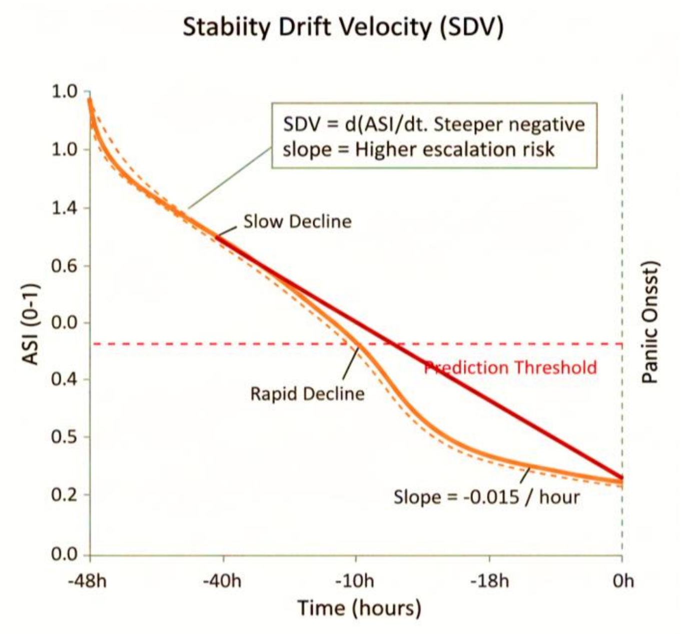


Figure 10: Stability Drift Velocity indicating acceleration of anxiety escalation.

The model predictive sensitivity was also improved by introducing environmental exposure-related variables. The elimination of such environmental characteristics contributed to suboptimal performance with an AUC of 0.86 and therefore supporting the contextual amplification theory drawn out in the environmental mental health literature [26-28]. The results indicate that environmental stressors are the modulators of the vulnerability of physiological processes, which increases instability in vulnerable individuals. The analysis of the features demonstrated that the most relevant ones were the deviation of the heart rate variability (HRV), the increase of the electrodermal activity (EDA), and the standard deviation of variance (SDV), which correspond to the existing research on the subject of autonomic dysregulation [3-6] and highlights the added value of the contextual modeling.

Ablation analysis showed that there was steady increase in performance with the succession of the inclusion of each modality as represented in Fig. 11. The witnessed improvement in AUC in models using physiological data only as opposed to the models using complete multimodal integration has underscored the theoretical basis of multimodal fusion [23] and has indicated the necessity to include physiological, behavioral and environmental clues when predicting panic reliably.

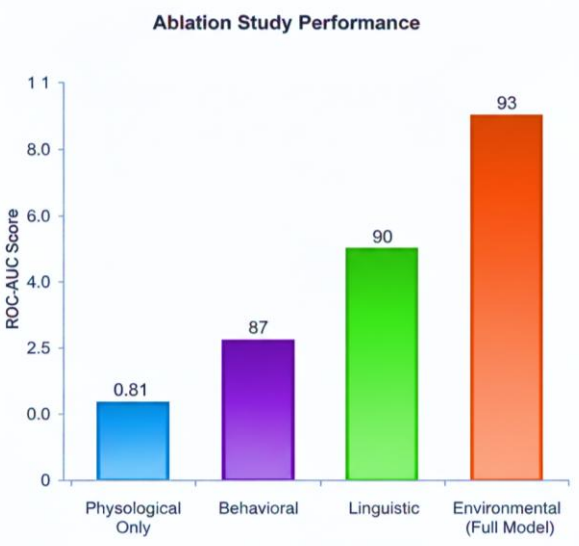


Fig. 11 Performance improvement across multimodal ablation stages

To conclude, the evidence shows that ongoing multimodal monitoring allows making a clinically significant early diagnosis of the panic episode and significantly outperforms unimodal and retrospective methods of assessment [1,2]. The proposed framework will switch the paradigm, which is mostly reactive with a predominance of symptoms, to a more proactive and precision-based model of dynamic instability modelling, combined with contextual environmental intelligence in the domain of digital psychiatry [12]. The combination of large predictive accuracy, large early detection windows and understandable feature contributions highlights a high degree of potential usefulness in clinical practice.

4. Conclusions

The current project presents a predictive multimodal digital aid that will be developed to prevent the development of anxiety exacerbations and possible panic attacks. That is why it promotes the transition to a non-retrospective report on psychiatric manifestations but proactive monitoring of mental health conditions. In this context, the Anxiety Stability Index (ASI) is suggested as a personalized, dynamic measure of emotional stability but operationalized as a synthesis of physiological indices, behavioral processes, linguistic signs and exposure to the environment in a consistent organization. The approach goes beyond the traditional diagnostic tests, and the concept of anxiety is objectively measured as a pattern of instability, which changes with time. The empirical evidence supports the theoretical assumption that panic episodes are characterized by minute, but identifiable changes in the autonomic regulation, behavioral variability, and exposure to contextual stressors. In line with the literature of previous psychophysiological applications, autonomic systems, such as heart-rate variability are an essential part of vulnerability detection, and multimodal fusion promotes predictive accuracy in line with digital phenotyping paradigms and multimodal learning hypotheses. The addition of Stability Drift Velocity (SDV) supplements the modern models by emphasizing dynamism of the escalation processes, instead of fixed risk rates, and supports the perception that anxiety development is a continuous, and not a discrete phenomenon. Another conceptual development is the use of environmental stress modelling. The framework provides a connection between contextual amplification strategies that are based on the environmental mental-health research and individual physiological sensitivity and exposure to external stressors. This interface of psychophysiology, contextual analysis and machine learning forms the basis of the new field of precision digital psychiatry. Notably, the suggested system will complement clinical judgement and not replace it. Using explainable modelling toolsets and interpretable feature-contribution models maintains transparency and enables integration even in hybrid human-AI care models. These systems are potentially capable of providing earlier intervention in healthcare, personalised tracking, and greater psychological strength in the long term. The study provides a foundation on which the anticipatory anxiety management could be performed, though, it should be conditional upon the subsequent longitudinal validations and large-scale deployment investigations. It is a trend of an even greater shift between reactive and proactive, personalised, and prevention-oriented psychiatric systems as a result of ongoing multimodal sensing, contextual modelling and adaptive machine learning. Overall, the research re-evaluates anxiety monitoring as an individual, dynamic and context-specific process. Combining physiological, behavioural, linguistic, and environmental aspects, the given framework provides a basis that the future digital ecosystem can use to identify the patterns of vulnerability before emergent panic, thus offering a new way of looking at active and accuracy-driven mental-health care.

Author Contributions

PS: Conceptualization, study design, analysis, data collection, methodology, software, resources, visualization. RM: Conceptualization, study design, analysis, data collection, methodology, software, resources, visualization, writing original draft, writing review and editing, and supervision. SD: Conceptualization, study design, analysis, data collection, methodology. SC: Software, resources, visualization, writing original draft, writing review and editing, and supervision. SM: Writing original draft, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

Acknowledgements

The authors recognise the interdisciplinary academic dialogues and technical assistance that aided in the conceptual advancement of this study. This research did not receive any external funding.

References

[1] Diagnostic A. statistical manual of mental disorders, (DSM-5) Washington. DC: American Psychiatric Association. 2013.

[2] Stein MB, Craske MG. Treating anxiety in 2017: optimizing care to improve outcomes. Jama. 2017 Jul 18;318(3):235-6. https://doi.org/10.1001/jama.2017.6996

[3] Barlow DH. Anxiety and its disorders: The nature and treatment of anxiety and panic. Guilford press; 2004 Jan 28.

[4] Craske MG, Kircanski K, Epstein A, Wittchen HU, Pine DS, Lewis-Fernández R, Hinton D. Panic disorder: a review of DSM-IV panic disorder and proposals for DSM-V. Depression and anxiety. 2010 Feb;27(2):93-112. https://doi.org/10.1002/da.20654

[5] Meuret AE, Rosenfield D, Hofmann SG, Suvak MK, Roth WT. Changes in respiration mediate changes in fear of bodily sensations in panic disorder. Journal of Psychiatric Research. 2009 Mar 1;43(6):634-41. https://doi.org/10.1016/j.jpsychires.2008.08.003

[6] Thayer JF, Åhs F, Fredrikson M, Sollers III JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012 Feb 1;36(2):747-56. https://doi.org/10.1016/j.neubiorev.2011.11.009

[7] Kreibig SD. Autonomic nervous system activity in emotion: A review. Biological psychology. 2010 Jul 1;84(3):394-421. https://doi.org/10.1016/j.biopsycho.2010.03.010

[8] Thayer JF, Lane RD. A model of neurovisceral integration in emotion regulation and dysregulation. Journal of affective disorders. 2000 Dec 2;61(3):201-16. https://doi.org/10.1016/S0165-0327(00)00338-4

[9] Chalmers JA, Quintana DS, Abbott MJ, Kemp AH. Anxiety disorders are associated with reduced heart rate variability: a meta-analysis. Frontiers in psychiatry. 2014 Jul 11;5:80. https://doi.org/10.3389/fpsyt.2014.00080

[10] Friedman BH. An autonomic flexibility-neurovisceral integration model of anxiety and cardiac vagal tone. Biological psychology. 2007 Feb 1;74(2):185-99. https://doi.org/10.1016/j.biopsycho.2005.08.009

[11] Kim HG, Cheon EJ, Bai DS, Lee YH, Koo BH. Stress and heart rate variability: a meta-analysis and review of the literature. Psychiatry investigation. 2018 Feb 28;15(3):235. https://doi.org/10.30773/pi.2017.08.17

[12] Insel TR. Digital phenotyping: technology for a new science of behavior. Jama. 2017 Oct 3;318(13):1215-6. https://doi.org/10.1001/jama.2017.11295

[13] Onnela JP, Rauch SL. Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. Neuropsychopharmacology. 2016 Jun;41(7):1691-6. https://doi.org/10.1038/npp.2016.7

[14] Torous J, Onnela JP, Keshavan M. New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. Translational psychiatry. 2017 Mar;7(3):e1053-. https://doi.org/10.1038/tp.2017.25

[15] Insel TR. Digital phenotyping: technology for a new science of behavior. Jama. 2017 Oct 3;318(13):1215-6. https://doi.org/10.1001/jama.2017.11295

[16] Onnela JP, Rauch SL. Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. Neuropsychopharmacology. 2016 Jun;41(7):1691-6. https://doi.org/10.1038/npp.2016.7

[17] Sano A, Picard RW. Stress recognition using wearable sensors and mobile phones. In2013 Humaine association conference on affective computing and intelligent interaction 2013 Sep 2 (pp. 671-676). IEEE. https://doi.org/10.1109/ACII.2013.117

[18] Gjoreski M, Gjoreski H, Luštrek M, Gams M. Continuous stress detection using a wrist device: in laboratory and real life. Inproceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing: Adjunct 2016 Sep 12 (pp. 1185-1193). https://doi.org/10.1145/2968219.2968306

[19] Garcia-Ceja E, Riegler M, Nordgreen T, Jakobsen P, Oedegaard KJ, Tørresen J. Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive and Mobile Computing. 2018 Dec 1;51:1-26. https://doi.org/10.1016/j.pmcj.2018.09.003

[20] Jacobson NC, Chung YJ. Passive sensing of prediction of moment-to-moment depressed mood among undergraduates with clinical levels of depression sample using smartphones. Sensors. 2020 Jun 24;20(12):3572. https://doi.org/10.3390/s20123572

[21] Hochreiter S, Schmidhuber J. Long short-term memory. Neural computation. 1997 Nov 15;9(8):1735-80. https://doi.org/10.1162/neco.1997.9.8.1735

[22] Breiman L, Forests R. Machine Learning. Vol. 45. The Netherlands: Kluwer Academic Publishers. 2001:5-32. https://doi.org/10.1023/A:1010933404324

[23] Baltrušaitis T, Ahuja C, Morency LP. Multimodal machine learning: A survey and taxonomy. IEEE transactions on pattern analysis and machine intelligence. 2018 Jan 25;41(2):423-43. https://doi.org/10.1109/TPAMI.2018.2798607

[24] Lundberg SM, Lee SI. A unified approach to interpreting model predictions. Advances in neural information processing systems. 2017;30.

[25] Doshi-Velez F, Kim B. Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608. 2017 Feb 28.

[26] Lederbogen F, Kirsch P, Haddad L, Streit F, Tost H, Schuch P, Wüst S, Pruessner JC, Rietschel M, Deuschle M, Meyer-Lindenberg A. City living and urban upbringing affect neural social stress processing in humans. Nature. 2011 Jun 23;474(7352):498-501. https://doi.org/10.1038/nature10190

[27] Pun VC, Kazemiparkouhi F, Manjourides J, Suh HH. Long-term PM2. 5 exposure and respiratory, cancer, and cardiovascular mortality in older US adults. American journal of epidemiology. 2017 Oct 15;186(8):961-9. https://doi.org/10.1093/aje/kwx166

[28] Evans GW. The built environment and mental health. Journal of urban health. 2003 Dec;80(4):536-55. https://doi.org/10.1093/jurban/jtg063

[29] Smuck M, Odonkor CA, Wilt JK, Schmidt N, Swiernik MA. The emerging clinical role of wearables: factors for successful implementation in healthcare. NPJ digital medicine. 2021 Mar 10;4(1):45. https://doi.org/10.1038/s41746-021-00418-3

[30] Healey JA, Picard RW. Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on intelligent transportation systems. 2005 Jun 30;6(2):156-66. https://doi.org/10.1109/TITS.2005.848368

[31] Das S, Chatterjee S, Karani AI, Ghosh AK. Stress detection while doing exam using eeg with machine learning techniques. InInternational Conference on Innovations in Data Analytics 2023 Nov 29 (pp. 177-187). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-97-4928-7_14

[32] Calvo RA, Milne DN, Hussain MS, Christensen H. Natural language processing in mental health applications using non-clinical texts. Natural Language Engineering. 2017 Sep;23(5):649-85. https://doi.org/10.1017/S1351324916000383

[33] Tausczik YR, Pennebaker JW. The psychological meaning of words: LIWC and computerized text analysis methods. Journal of language and social psychology. 2010 Mar;29(1):24-54. https://doi.org/10.1177/0261927X09351676

[34] Sabry F, Eltaras T, Labda W, Alzoubi K, Malluhi Q. Machine learning for healthcare wearable devices: the big picture. Journal of Healthcare Engineering. 2022;2022(1):4653923. https://doi.org/10.1155/2022/4653923

[35] Acheampong FA, Wenyu C, Nunoo-Mensah H. Text-based emotion detection: Advances, challenges, and opportunities. Engineering Reports. 2020 Jul;2(7):e12189. https://doi.org/10.1002/eng2.12189

[36] Tarassenko L, Clifton DA, Pinsky MR, Hravnak MT, Woods JR, Watkinson PJ. Centile-based early warning scores derived from statistical distributions of vital signs. Resuscitation. 2011 Aug 1;82(8):1013-8. https://doi.org/10.1016/j.resuscitation.2011.03.006

[37] Lin X, Luo J, Liao M, Su Y, Lv M, Li Q, Xiao S, Xiang J. Wearable sensor-based monitoring of environmental exposures and the associated health effects: A review. Biosensors. 2022 Dec 6;12(12):1131. https://doi.org/10.3390/bios12121131

[38] Riley RD, van der Windt D, Croft P, Moons KG, editors. Prognosis research in healthcare: concepts, methods, and impact. Oxford University Press; 2019 Jan 17. https://doi.org/10.1093/med/9780198796619.001.0001

[39] Steyerberg EW, Harrell Jr FE. Prediction models need appropriate internal, internal-external, and external validation. Journal of clinical epidemiology. 2015 Apr 18;69:245. https://doi.org/10.1016/j.jclinepi.2015.04.005

[40] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S, Dean J. A guide to deep learning in healthcare. Nature medicine. 2019 Jan;25(1):24-9. https://doi.org/10.1038/s41591-018-0316-z

[41] Ghosh A, Diyasi S, Chatterjee S. Enhancing SQL Injection Prevention: Advanced Machine Learning and LSTM-Based Techniques. International Journal on Computational Modelling Applications. 2024 Jul 31;1(1):20-31. https://doi.org/10.63503/j.ijcma.2024.16

[42] World Health Organization. WHO consultation towards the development of guidance on ethics and governance of artificial intelligence for health: meeting report, Geneva, Switzerland, 2-4 October 2019. World Health Organization; 2021.

[43] Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nature machine intelligence. 2019 Sep;1(9):389-99. https://doi.org/10.1038/s42256-019-0088-2

[44] Hoofnagle CJ, Van Der Sloot B, Borgesius FZ. The European Union general data protection regulation: what it is and what it means. Information & communications technology law. 2019 Jan 2;28(1):65-98. https://doi.org/10.1080/13600834.2019.1573501

[45] Esteva A, Robicquet A, Ramsundar B, Kuleshov V, DePristo M, Chou K, Cui C, Corrado G, Thrun S, Dean J. A guide to deep learning in healthcare. Nature medicine. 2019 Jan;25(1):24-9. https://doi.org/10.1038/s41591-018-0316-z

[46] Pun VC, Manjourides J, Suh H. Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study. Environmental health perspectives. 2016 Aug 12;125(3):342. https://doi.org/10.1289/EHP494

[47] Huckvale K, Torous J, Larsen ME. Assessment of the data sharing and privacy practices of smartphone apps for depression and smoking cessation. JAMA network open. 2019 Apr 5;2(4):e192542. https://doi.org/10.1001/jamanetworkopen.2019.2542