

Chapter 3

IA Multimodal Platform for Objective Pain Measurement

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Abstract

Pain remains a complex and pervasive clinical challenge, affecting patient quality of life and healthcare systems worldwide. Current assessments rely on subjective self-reports, which are limited by perception, communication barriers, and emotional factors. Recent advances suggest physiological biomarkers, such as electrodermal activity and heart rate variability, can serve as objective indicators by reflecting autonomic responses. However, an integrated, multimodal system combining biomedical signals from wearable devices for real-time objective pain detection has yet to be fully developed. Building on this, our project's focused on building an AI-powered pain index that complements or replaces subjective scales, enabling better clinical decisions especially for infants and those unable to communicate, thus advancing precision pain medicine and improving patient outcomes.

Keywords: *Personalised medicine, Biomedical data, AI-modelling, Pain index*

Introduction

Pain remains a complex and widespread challenge in medicine, affecting quality of life and healthcare resources globally. Defined by ICD-11¹, pain is classified as acute or chronic, with acute pain warning of injury and resolving within months, while chronic persists beyond healing². Whether chronic or acute we still understand very little about pain, and no clear biomarkers are currently used for diagnosis or management. Current assessment methods predominantly rely on subjective self-report scales, such as the numerical rating scale (NRS) and the visual analogue scale (VAS), which are inherently limited by individual perception (communication barriers/emotional states), especially in populations unable to communicate, such as infants or neurological patients³.

¹Joanna R. Rozisky et al., "Modified Non-invasive Brain Stimulation in Fibromyalgia." "Modified Non-invasive Brain Stimulation in Fibromyalgia." *Journal of Pain and Relief* 3, no. 4 (Jan 2014): 1–7.

<https://doi.org/10.4172/2167-0846.1000149>

²Daniel S. Goldberg and Summer J. McGee, "Pain as a Global Public Health Priority," *BMC Public Health* 11, no. 770 (October 6, 2011), <https://doi.org/10.1186/1471-2458-11-770>

³R. Cowen et al., "Assessing Pain Objectively: The Use of Physiological Markers," *Anaesthesia* 70, no. 7 (2015): 828–47, <https://doi.org/10.1111/anae.13018>

Recent advances suggest that physiological biomarkers, such as electroencephalogram (EEG)⁴, electrodermal activity (EDA)⁵, heart rate variability (HRV)⁶, respiratory rate (RR)⁷, blood saturation⁸, and body temperature (T)⁹, may serve as objective indicators of pain by reflecting autonomic nervous system responses. However, an integrated system combining these signals from wearable devices remains undeveloped. Taking this into account, our initiative aims to create an AI-powered, multimodal platform that uses wearable sensors, like smartwatches, to provide real-time, objective pain assessment. This approach promises to improve diagnosis, monitoring, and pain management across diverse clinical settings. Existing studies have demonstrated correlations between individual autonomic biomarkers and pain states¹⁰⁻¹². We focus on autonomic responses and behavioural perceptions for a more accurate and robust pain index¹³ that will enable us to detect and quantify pain through smart wearables. We consider utilising smartwatches due to being among the most widely adopted wearables globally with over 200 million smartwatches being sold annually worldwide¹⁴. The current manuscript outlines our approach what has been achieved up to today and how we aim to finalise the development of our pain index platform to improve pain care.

Proposed Methodology

Phase 1: Open data sets AI modelling

We have successfully completed the first phase, including a literature review on machine learning (ML)

⁴Abeer Al-Nafjan, Hadeel Alshehri, and Mashael Aldayel, "Objective Pain Assessment Using Deep Learning Through EEG-Based Brain-Computer Interfaces," *Biology* 14, no. 2 (February 17, 2025): 210, <https://doi.org/10.3390/biology14020210>

⁵Viprali Bhatkar, Rosalind Picard, and Camilla Staahl, "Combining Electrodermal Activity With the Peak-Pain Time to Quantify Three Temporal Regions of Pain Experience," *Frontiers in Pain Research* 3, 764128 (March 23, 2022), <https://doi.org/10.3389/fpain.2022.764128>

⁶Giuseppe Forte et al., "Heart Rate Variability and Pain: A Systematic Review," *Brain Sciences* 12, no. 2 (January 24, 2022): 153, <https://doi.org/10.3390/brainsci12020153>

⁷Hassan Jafari et al., "Pain and Respiration: A Systematic Review," *Pain* 158, no. 6 (January 30, 2017): 995–1006, <https://doi.org/10.1097/j.pain.0000000000000865>

⁸Lars Ø. Høiseith et al., "Tissue Oxygen Saturation and Finger Perfusion Index in Central Hypovolemia," *Critical Care Medicine* 43, no. 4 (2015): 747–56, <https://doi.org/10.1097/ccm.0000000000000766>

⁹Alice A. Larson, José V. Pardo, and Jeffrey D. Pasley, "Review of Overlap Between Thermoregulation and Pain Modulation in Fibromyalgia," *Clinical Journal of Pain* 30, no. 6 (2014): 544–55, <https://doi.org/10.1097/ajp.0b013e3182a0e383>

¹⁰Cowen et al., "Assessing Pain Objectively: The Use of Physiological Markers."

¹¹Reed Larson and Mihaly Csikszentmihalyi, "The Experience Sampling Method." In *Flow and the Foundations of Positive Psychology*, editing by Mihaly Csikszentmihalyi. Springer, 2014.

¹²Larson, Pardo, and Pasley. "Review of Overlap Between Thermoregulation and Pain Modulation in Fibromyalgia."

¹³Brandon N Kyle and Daniel W McNeil, "Autonomic Arousal and Experimentally Induced Pain: A Critical Review of the Literature," *Pain Research and Management* 19, no. 3 (2014): 159–67, <https://doi.org/10.1155/2014/536859>

¹⁴Michael R Massoomi and Eileen M Handberg, "Increasing and Evolving Role of Smart Devices in Modern Medicine," *European Cardiology Review* 14, no. 3 (December 18, 2019): 181–86, <https://doi.org/10.15420/ecr.2019.02>

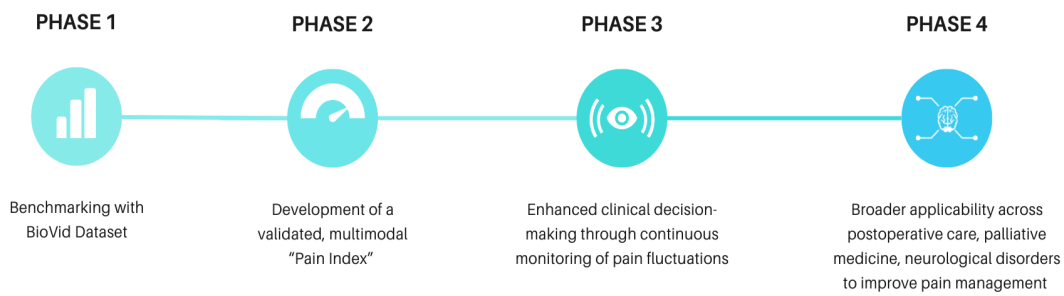


Figure 1: Illustration of the four phases in the methodology.

algorithms and convolutional neural networks (CNNs) for automated pain assessment. During this stage, we developed a preliminary model using public research data, in collaboration with the Rochester Institute of Technology Dubai. During this initial phase, we tested an AI-driven pain assessment model, which will be used in phase 2 and phase 3 of the study with real world data (healthy subjects and clinical setting). We primarily focused on two key public datasets: BioVid Heat Pain Database (Part B) and X-ITE Pain Challenge 2025 dataset that offer controlled pain stimuli and multimodal physiological data. We emphasised on biosignals data (EDA, ECG, EMG) within the datasets, excluding behavioural data which can be key to minimising the risk of false positives, with a primary focus on physiological parameters.

Phase 2: Human testing (healthy subjects)

In phase 2 we aim to evaluate the platform's ability to detect experimentally induced acute pain through cold pressor task (submerging their dominant hand in cold water). Key objectives include optimising sensor integration, refining data collection protocols, and conducting initial model training in healthy subjects, aged 18–60 of all genders. They will be asked to wear a smartwatch, and their pain levels will be assessed through an eVAS, with the pain intensities categorised into four levels. This serves as a validation for the development of the AI model.

Phase 3: Clinical evaluation (acute pain model)

This phase involves validating the platform in real-world clinical settings by monitoring postoperative patients during their recovery. The goal is to assess how the pain index correlates with patient perceptions and the overall recovery process, evaluating the real-time features of our pain index and its impact in immediate clinical decisions and personalised pain management.

Phase 4: Adaptation for chronic pain assessment

This last phase aims to translate the acute pain index to evaluate and monitor patients suffering from chronic pain conditions, such as cancer-related pain. Cancer related pain is an appropriate model to

assess complex acute and chronic pain simultaneously, due to its complex nature¹⁵. Our objective is to investigate how to translate what is observed in acute pain, into chronic pain modelling, considering that chronic pain often involves blunted or dysregulated physiological responses. This will enable us to determine whether the pain index can also become a reliable tool to help objectify the complex autonomic dynamics associated with chronic pain states.

Results

Benchmarking with the BioVid dataset

We evaluated standard ML pipelines such as AdaBoost, XGBoost, and Random Forest on the BioVid dataset to have an insight on their performance in classifying pain levels based on engineered signal features.

Participation in the X-ITE Pain Challenge 2025

To widen our understanding on pain data, we participated in the X-ITE Challenge 2025, which addressed the classification of LOW and MODERATE pain levels. We focused on analysing the challenges in pain classifications. This involvement helped us assess the behaviour of XGBoost and LightGBM models.

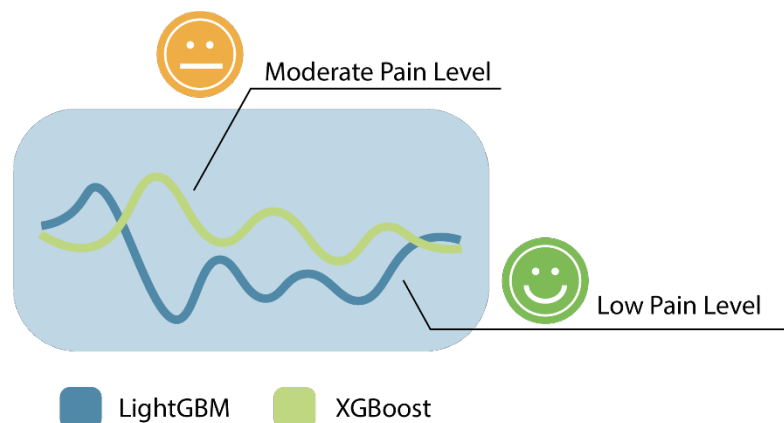


Figure 2: Representation of pain model.

Discussion

Random Forest achieved the highest accuracy (98.63%) in our initial analysis using only noise reduction on the BioVid dataset. After incorporating modality-specific feature extraction, the best models shifted to AdaBoost for ECG (85.8%), XGBoost for EMG (85.0%), and AdaBoost for GSR (76.9%). This performance change underscores the value of physiologically meaningful, modality-tailored features, despite the overall drop in accuracy. While only cross-validation accuracy is reported here, future work will include additional metrics such as F1-score and AUC for a more comprehensive evaluation.

¹⁵Rianne De Wit et al., “Assessment of Pain Cognitions in Cancer Patients With Chronic Pain,” *Journal of Pain and Symptom Management* 22, no. 5 (November 1, 2001): 911–24, [https://doi.org/10.1016/s0885-3924\(01\)00354-2](https://doi.org/10.1016/s0885-3924(01)00354-2)

Clinical Considerations

In Phases 2, 3, and 4 we anticipate the following outcomes:

- Firstly, to be able to develop a validated, multimodal “pain index” that surpasses subjective scales in reliability and objectivity.
- Second, to enhance clinical decision-making through continuous monitoring of pain fluctuations. We envision a broader applicability across settings from postoperative care, palliative medicine to neurological disorders, improving pain management in underserved populations. Wearable technology will contribute to the advancement of personalized medicine, with data-driven insights guiding tailored interventions.

Conclusion

This overview aims to lay the foundation for an objective, multimodal pain index platform based on integrating wearable sensors, AI, and robust clinical validations. This innovation would enable continuous and objective pain assessment, especially for those unable to communicate, transforming pain care worldwide and improving quality of life.

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