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POS0257 PAINWAVES: THE POTENTIAL OF MACHINE LEARNING TO DIFFERENTIATE CHRONIC PAIN COHORTS USING ELECTROENCEPHALOGRAPHY

Keywords: Pain, Imaging, Artificial Intelligence

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Background: Chronic pain is highly prevalent, debilitating and lacks effective treatments. Experimental and neuroimaging research demonstrates abnormal central pain processing[1]. However, robust brain-based biomarkers that could inform targeted treatments are lacking. Electroencephalography (EEG) is the optimal tool to investigate dynamic abnormalities in pain processing to reveal underlying mechanisms. Early evidence from EEG studies in Fibromyalgia (FM) indicate potential mechanisms such as thalamocortical dysrhythmia[2], demonstrated by alterations in the Alpha and Theta frequency bands. However, existing studies employ rudimentary analyses failing to account for the multivariate and temporal nature of EEG data. State-of-the-art machine learning (ML) approaches provide unique opportunities to generate a deeper understanding of EEG signatures in chronic pain and identify specific biomarkers that could be used to differentiate mechanistic subtypes.
Objectives: This preliminary work aims to establish whether a state-of-the-art ML classifier can differentiate patients with FM from healthy controls based on their EEG characteristics.
Methods: The dataset used was collected through The VIPA Study (ISRCTN46681140). Patients with FM satisfied the 2016 FM classification criteria. High-density 64-channel EEG data using an electrolyte gel-based active electrode system was collected at rest with participants' eyes closed over 2 minutes. Individual Fast Fourier Transforms were applied to overlapping time windows to extract EEG frequency band power whilst retaining temporal information. Frequency bands were used as features to train a classification model (definitions of frequency ranges in Table 1). One of the fastest, most accurate state-of-the-art time-series classification ML algorithms (mini-ROCKET) was used via the sktime python toolkit. To obtain unbiased accuracy estimates across all participants, a 'leave-one-out' strategy was used. Accuracy of the algorithm was reported; defined by the number of correct predictions divided by the total number of predictions for each frequency band (2-class problem, chance estimates 0.5-0.6 based on $p<0.05$).
Results: Data from 23 patients with FM (mean age 46 ±14yrs, 87% female) and 14 healthy controls (mean age 71 ±7yrs, 50% female) were analysed. Patients with FM had moderate self-reported pain (5.5 ±2.3 VAS) and disease severity (mean FIQR 65.4 ±16.6) at baseline. Theta and Alpha were the most discriminatory frequency bands, with mini-ROCKET able to classify participants with 70.7% accuracy. The Beta frequency band was less discriminatory (63.4%) but still above predicted chance estimates. Delta frequency band was least discriminatory (51.2%).
Conclusion: Preliminary results indicate that machine learning can be successfully used to differentiate patients with Fibromyalgia from healthy controls based on EEG measures of the Alpha and Theta frequency bands. Alterations in Alpha and Theta have been demonstrated in previous non-ML research, indicating potential underlying abnormalities in the interaction between the thalamus and cortex which may be related to central mechanisms underlying chronic pain. Further work is required in larger, matched cohorts to validate these findings, but this early work highlights the future potential of EEG and ML in both understanding brain-based pain mechanisms and using EEG features to differentiate chronic pain subgroups.

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Table 1. Classifier accuracy across the EEG frequency bands (FM vs Control)

Frequency Band	Accuracy of mini-ROCKET classifier
Delta (2-4hz)	0.512 (51.2%)
Theta (4-8hz)	0.707 (70.7%)
Alpha (8-12hz)	0.707 (70.7%)
Beta (12-30hz)	0.634 (63.4%)
Gamma (30-40hz)	0.610 (61.0%)

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POS0258 USING REAL-TIME PATIENT-GENERATED DATA FROM MOBILE HEALTH DEVICES TO CHARACTERISE PAIN FLARES IN RHEUMATOID ARTHRITIS

Keywords: Pain, Rheumatoid arthritis

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Background: Pain flares in rheumatoid arthritis (RA) often refer to episodes of increased pain severity accompanied by pain impact. Describing the prevalence and predictors of pain flare occurrence is difficult since there are no agreed classification criteria[1]. Patient-generated data collected in real-time with mobile health (mHealth) devices provide an opportunity to identify individual patterns and triggers in pain dynamics over time[2].
Objectives: We aim to characterise pain flares and pre-flare exposures using real-time mHealth data from patients with RA.
Methods: In a 30-day mHealth study[3] we collected daily reports of pain severity on a five-point scale (ranging from none to very severe pain) via a smartphone app to define the onset and ending criteria for three types of pain flares, including 1) above average: pain severity greater than the personal median score, 2) significant change: two-point increase in pain severity from yesterday, and 3) absolute impact: two-point increase in pain severity from yesterday and pain severity greater than three. All pain flare types end when pain severity returns to the personal median score or lower. Exposures of the preceding periods were self-rated sleep quality, mood, anxiety and fatigue (all scales range 1-5, higher scores are worse) using the same study app, and passively recorded total time asleep (hr), sleep efficiency (%), sleep latency (min) and physical activity (min) via a wrist-worn accelerometer. We report the 30-day monthly pain flare rate, the average duration of pain flares and summarise average exposures one-day and three-day before pain flare onset.
Results: We analysed 253 participants who provided at least seven days of data (81.8% females; mean age = 59.9, average years with RA = 12.1). A total of 6,244 daily reports were included in the analysis. Pain flare occurrence decreased when applying more complex definitions. 31% of participants had pain flares under the most stringent definition of absolute impact, with two episodes per month (Table 1). Across all types, 75% of pain flares lasted two days before returning (Median = 1, IQR = 1-2) but could persist up to 11 days (Figure 1). Pre-flare exposures did not differ between pain flare types nor between the preceding periods. Participants reported fair sleep quality (Median = 3), feeling quite happy (Median = 2), not anxious (Median = 1) and mild fatigue (Median = 2) prior to pain flare onset. Objective exposures showed a daily average of 7-hour sleep with 83% efficiency, under 20 minutes to fall asleep, and approximately 50 minutes being active.

Table 1. Pain flare characteristics

Type	Number of participants with ≥1 pain flare(s) (%)	Total number of pain flares	Monthly pain flare rate (SD)
Above average	224 (88.5)	788	4.3 (2.2)
Significant change	108 (42.7)	171	2.0 (1.1)
Absolute impact	78 (30.8)	116	2.0 (1.1)