Journal of Pain Research

Dovepress
Taylor & Francis Group

Open Access Full Text Article

ORIGINAL RESEARCH

The Investigation of the Relationship Between Individual Pain Perception, Brain Electrical Activity, and Facial Expression Based on Combined EEG and Facial EMG Analysis

Chaozong Ma[1,2,*], Chenxi Wang[3,*], Dan Zhu[1], Mingfang Chen[1], Ming Zhang[1,4], Juan He[1]

[1]Department of Rehabilitation Medicine, First Affiliated Hospital of Xi'an Jiaotong University, Xi'an, People's Republic of China; [2]Military Medical Psychology School, Fourth Military Medical University, Xi'an, People's Republic of China; [3]Center for Brain Imaging, School of Life Science and Technology, Xidian University, Xi'an, People's Republic of China; [4]Department of Medical Imaging, First Affiliated Hospital of Xi'an Jiaotong University, Xi'an, People's Republic of China

*These authors contributed equally to this work

Correspondence: Ming Zhang; Juan He, Email zhangming01@mail.xjtu.edu.cn; hejuan198553@126.com

Purpose: Pain is a multidimensional, unpleasant emotional and sensory experience, and accurately assessing its intensity is crucial for effective management. However, individuals with cognitive impairments or language deficits may struggle to accurately report their pain. EEG provides insight into the neurological aspects of pain, while facial EMG captures the sensory and peripheral muscle responses. Our objective is to explore the relationship between individual pain perception, brain activity, and facial expressions through a combined analysis of EEG and facial EMG, aiming to provide an objective and multidimensional approach to pain assessment.

Methods: We investigated pain perception in response to electrical stimulation of the middle finger in 26 healthy subjects. The 32-channel EEG and 3-channel facial EMG signals were simultaneously recorded during a pain rating task. Group difference and correlation analysis were employed to investigate the relationship between individual pain perception, EEG, and facial EMG. The general linear model (GLM) was used for multidimensional pain assessment.

Results: The EEG analysis revealed that painful stimuli induced N2-P2 complex waveforms and gamma oscillations, with substantial variability in response to different stimuli. The facial EMG signals also demonstrated significant differences and variability correlated with subjective pain ratings. A combined analysis of EEG and facial EMG data using a general linear model indicated that both N2-P2 complex waveforms and the zygomatic muscle responses significantly contributed to pain assessment.

Conclusion: Facial EMG signals provide pain descriptions which are not sufficiently captured by EEG signals, and integrating both signals offers a more comprehensive understanding of pain perception. Our study underscores the potential of multimodal neurophysiological measurements in pain perception, offering a more comprehensive framework for evaluating pain.

Keywords: pain assessment, electroencephalogram, facial electromyogram, multiple physiological signals, general linear model

Introduction

Pain perception is subjective and dependent on individual differences in physiological, emotional, and cognitive states.[1,2] The precise evaluation of pain intensity is crucial for effective pain management.[3,4] Self-report is widely regarded as the gold standard for pain assessment[5] with tools like the Visual Analog Scale (VAS) asking patients to mark their pain intensity on a 10 cm line, where one end representing "no pain" and the other end representing "the worst possible pain.[6] However, individuals with cognitive impairments or language deficits may struggle to accurately report their pain. Additional, pain is a multidimensional, unpleasant emotional and sensory experience, the neural signals reflecting the

Received: 10 May 2024
Accepted: 11 December 2024
Published: 3 January 2025

variability in pain perception across individuals remain elusive. Therefore, the objective and multidimensional pain assessment is crucial for pain management.

Electroencephalography (EEG) can identify synchronized neuronal activity that occurs spontaneously in response to painful stimuli, which has been proven to be valuable in accurately evaluating the degree of pain.[7] The biphasic vertex wave, which is triggered by transient nociceptive stimuli, has the capacity to differentiate the levels of perceived pain.[8–10] Hu et al found that gamma-band event-related synchronization can serve as a unique electrophysiological indicator for differentiating between responses to equally salient auditory, visual, and somatosensory stimuli versus those activated by nociceptive stimuli.[11,12]

The presence of pain is frequently accompanied by physiological responses, encompassing enhanced heart rate, dilated pupil size, increased respiratory rate, and the occurrence of facial grimaces.[13–16] In clinical and experimental pain research, facial expression has garnered significant focus and offers the most specific and sensitive nonverbal indicators for pain.[17–19] The facial expression of pain is characterized by the lowering of the eyebrows, squeezing of the eyes, wrinkling of the nose, raising of the upper lip, and opening of the mouth.[19,20] Consistent facial expressions were discovered in response to diverse forms of experimental pain stimuli in healthy subjects.[21] Researchers have also noted that individuals with chronic pain exhibit the same facial expressions as those experiencing experimental pain.[21–23] These observations imply a potential link between facial movements and pain perception.

Recent advances in imaging techniques allow for the simultaneous monitoring of multiple physiological signals, which together offer a more nuanced understanding of pain. Previous studies have explored multimodal approaches, integrating neurophysiological data with behavioral signals to improve pain assessment.[24] For instance, a study involving electrodermal activity (EDA), photoplethysmography (PPG), and respiration (RESP) signals found EDA to be the most informative sensor under pain conditions.[25] Additionally, machine learning approaches applied to bio-signals like EMG, GSR, and ECG have shown promise in classifying pain levels and differentiating pain intensities.[26] These studies have focused on combining various physiological signals, few have specifically explored the integration of EEG with facial EMG. While EEG provides a direct measure of the brain's response to pain, while facial expressions which can be assessed using EMG, reflects the motor responses to pain. Combining these signals can capture both the sensory and peripheral muscle components of pain.[27]

In this study, we hypothesized that both EEG and facial EMG signals are linked to individual differences in pain perception and integrating these signals would account for greater pain variability than single signal. Our objective is to explore the relationship between individual pain perception, brain activity, and facial expressions through a combined analysis of EEG and facial EMG, with the aim of offering an objective and multidimensional approach to pain assessment. To this end, simultaneous recordings of a 32-channel EEG and a 3-channel facial EMG were obtained from healthy subjects subjected to two distinct pain intensities. A general linear model was employed to assess the contributions of EEG and facial EMG signals in the evaluation of individual pain perception.

Materials and Methods

The research aims and experimental procedures had been fully explained to all participants, and the written informed consent of all participants was obtained. All studies were conducted in accordance with the Declaration of Helsinki and were approved by the Institutional Review Board of the First Affiliated Hospital of the Medical College at Xi'an Jiaotong University.

Participants

Healthy subjects were recruited from the local community. In this investigation, 26 individuals were initially recruited. Due to incomplete laboratory measurements, a subset of participants was excluded, resulting in data from 24 subjects being analyzed (13 females and 11 males, averaging 20.5±1.8 years in age). Exclusion criteria were: (1) individuals with any physical illness, such as a brain tumor, hepatitis, or epilepsy, as assessed according to clinical evaluations and medical records; (2) those with the existence of chronic pain conditions (eg, tension-type headache, fibromyalgia, etc).; (3) those with the existence of a neurological disease or psychiatric disorder; (4) pregnancy; (5) those using prescription medications within the last month; (6) those with alcohol, nicotine, or drug abuse; and (7) those with claustrophobia.

Nociceptive Stimulation and Experimental Design

Figure 1A illustrates the data acquisition process, where synchronized EEG and facial EMG data were captured from participants using two 32-channel Tmsi SAGA devices (pass band: 1–100 hz; sampling rate: 1000 hz). Nociceptive somatosensory stimuli were delivered using an electrical stimulator (pulse duration: 50 ms; SXC-4A, Sanxia Technique Inc., China) with constant-current square-wave electrical pulses. The application of these electrical pulses was conducted through surface electrodes positioned on the upper side of the proximal phalanx of the left middle finger.

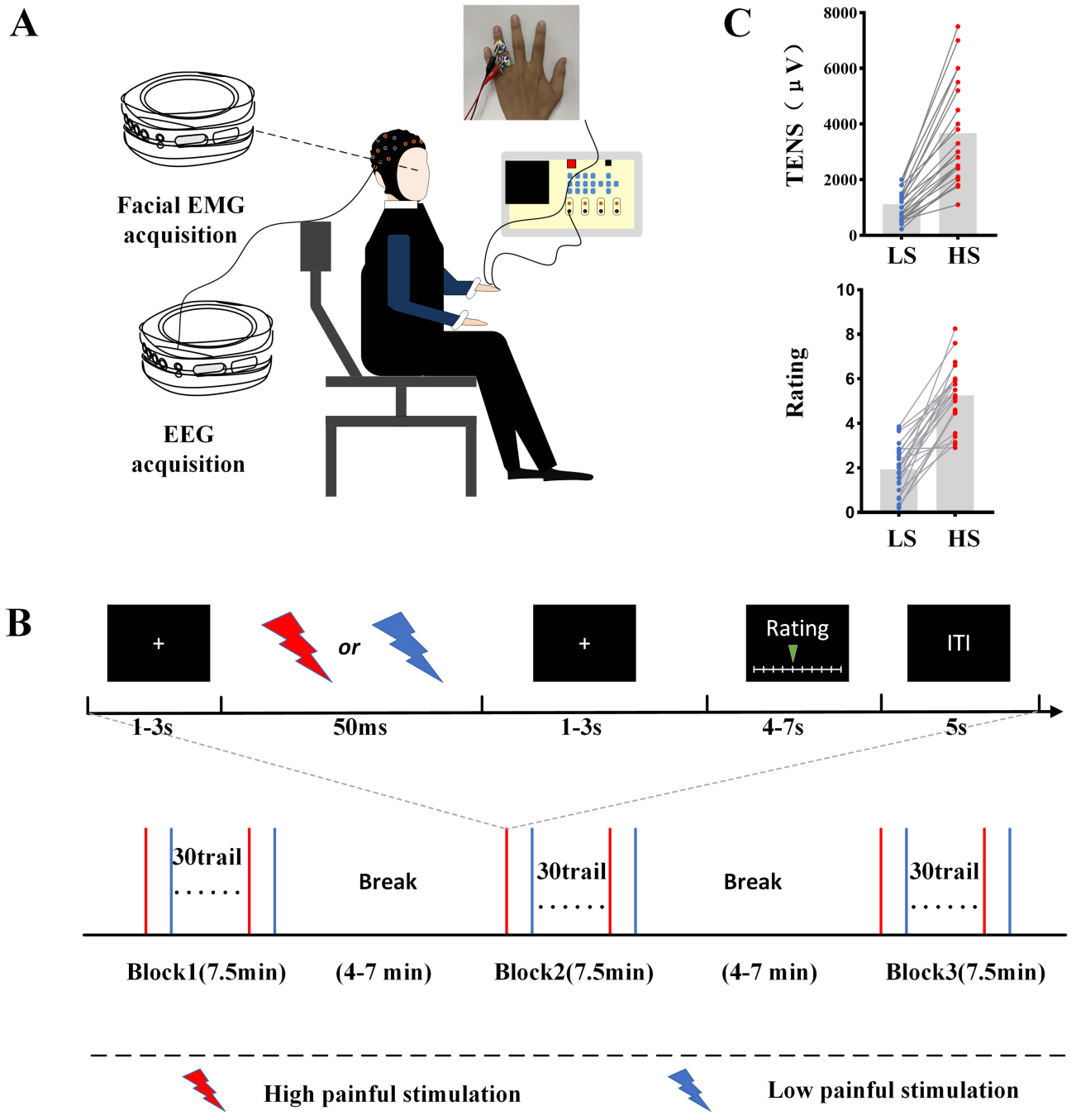

Figure 1 Experimental design and procedure. (**A**) The electrical pulse travels through a pair of surface electrodes placed at the upper side of the proximal phalanx of the left middle finger, while a 32-channel EEG and a 3-channel EMG were simultaneously collected. (**B**) Two stimulation types (low pain and high pain) were included in the experiment. Each electrocutaneous stimulation lasted 50 ms. (**C**) Pain threshold and subjective ratings of pain perception are shown in the up and down panels, respectively.
Abbreviation: LS, low stimuli; HS, high stimuli.

https://doi.org/10.2147/JPR.S477658

At least 24 hours before the EEG and facial EMG recording, participants were subjected to electrical stimuli of varying intensities, with their pain responses quantified using a 0–10 numerical rating scale (NRS), where 0 indicated no pain and 10 represented the maximum tolerable pain. To establish a baseline for low and high pain thresholds, participants initially acclimated to the stimuli. The ascending method of limits was utilized to ascertain the stimulus intensity corresponding to "low pain" (NRS score of 2) and "high pain" (NRS score of 6). This involved gradually increasing the current starting at 0.2 mA in increments of 0.1 mA. Subjects were instructed to verbally report pain scores to assess the intensity of pain perception. This procedure was repeated three times for each participant, and the averaged stimulus intensities were calculated for the following experiment. This process determines the subject's high or low pain threshold for the formal experiment.

The experimental procedure, as depicted in Figure 1B. Each participant underwent three blocks, with each block entailing the administration of 15 low-pain and 15 high-pain stimuli in a pseudorandom sequence. Hence, each participant completed 45 high-intensity and 45 low-intensity stimuli per condition. Each trial commenced with the display of a fixation cross for a duration of 1–3 seconds, followed by the administration of either a low or high pain stimulus. Subsequently, a scoring interface emerged on the screen 1–3 seconds post-stimulus, where participants were allotted a 5-second window to verbally rate their perceived pain (0–10 scores). There is a 4–7s black screen at the end. This resulted in an approximate inter-trial interval of 15 seconds. During the experiment, participants were seated comfortably in a quiet room, focusing on discerning and reporting the perceived intensity of each pain stimulus. Throughout these sessions, data from three facial EMG channels and 32 EEG channels were simultaneously recorded.

Data Collection and Preprocessing

EEG signals were recorded using 32 Ag-AgCl scalp electrodes placed according to the International 10–20 system. The left mastoid (M1) was used as the online reference, and all electrode impedances were kept lower than 10 kΩ. EEG data were pre-processed using MATLAB and the open-source toolbox EEGLAB.[28,29] EEG data were band-pass filtered between 1 and 100 hz, and EEG epochs were extracted using a time window of 1500 ms (500 ms before and 1000 ms after stimulus onset). The baseline was corrected using the pre-stimulus interval. Afterwards, independent component analysis (ICA) was applied to remove eye blinks and movements from the data.

The EMG electrodes were placed on the corrugator supercilii (CS), labialis levator (LL), and zygomaticus (ZM) along the right side of the face. A reference electrode was placed on the bony area behind the ear.[30] The facial skin under the electrodes was cleaned using cleansing swabs with 75% alcohol before the electrode placement. EMG data were processed with a 10–200 hz Butterworth pass filter to remove movement artifacts and baseline drifts. Adaptive filters were used to remove power-frequency interference at 50 hz.

EEG Features Extraction

For each participant, epochs belonging to the same stimulus intensity were averaged, yielding two average waveforms with time locked to the stimulus onset. N2 and P2 waves, defined as the most negative and positive deflections between 100 and 500 ms after stimulus onset, were measured at Cz for each subject and stimulus intensity.[31,32] The amplitudes of the N2 and P2 waves of pain-related potentials were assessed by averaging single-trial amplitude values across predefined time windows. Group-level scalp topographies at the peak latency of all waves were computed by spline interpolation.

For the conversion of EEG data from the temporal to the time-frequency domain, a windowed Fourier transform (WFT) with a fixed 300-ms Hanning window was utilized. For each epoch, the WFT algorithm yielded a complex time-frequency estimate F (t, f) at each time-frequency point (t, f), which extended from −500 to 1000 ms (in steps of 1 ms) in the time domain and from 1 to 100 hz (in steps of 1 hz) in the frequency domain. Baseline correction was conducted during the pre-stimulus interval, ranging from −350 to −150 milliseconds relative to the onset of the stimulus.[33] Subsequently, time-frequency data for each participant were averaged across trials for both stimulus types. The statistical analyses were predominantly focused on two time-frequency regions of interest (ROIs) within the alpha-band event-related desynchronization (α-ERD) and gamma-band event-related synchronization (γ-ERS). These regions have been

previously established as pertinent to variations in stimulus intensity and pain perception.[12,34] For each ROI, the power was averaged across both time and frequency dimensions.

EMG Features Extraction

The descriptive statistics of the variables of EMG strength were calculated, such as mean absolute value (MAV), variance (VAR), and log detector (LOG). MAV is the mean value of the absolute amplitude of the signal processed by the time window method.[35]

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i|$$

Variance of EMG reflects the concentration and dispersion of the signal data value.[36]

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N}x_i^2$$

Log detector is generally used to estimate the contractility of muscle, which can be defined as.[37]

$$LOG = e^{\frac{1}{N}\sum_{i=1}^{N}log|x_i|}$$

For the above measurements, where represents the EMG signal in a segment and denotes length of the EMG signal.

Statistical Analyses

To compare the differences in EEG and EMG measurements between low- and high-pain stimuli, paired t-tests were used. For multiple comparisons, a false discovery rate (FDR) procedure was adopted to adjust the p values. Pearson's correlation was performed between the ratings of perceived pain and a series of variables, including: (1) EEG responses (ie, N2 and P2 amplitudes), (2) EEG oscillations (ie, α-ERD and γ-ERS), and (3) EMG features (ie, MAV, VAR, and LOG). In addition, general linear modeling was implemented to assess the contribution of both EEG and facial EMG signals in discerning individual variances in pain perception.

Results

Pain Threshold and Subjective Ratings of Pain Perception

Figure 1C shows the behavioral results of pain threshold and subjective ratings of pain perception. It was observed that the threshold for high pain (3669±584.6 mA) was significantly higher (t = 8.99, p = 5.401e-09) than that for low pain (1114±174.3 mA). Similarly, subjective evaluations for high-intensity stimuli (5.25±1.39) were significantly greater (t = 10.71, p = 2.067e-10) than those for low-intensity stimuli (1.94±1.10).

EEG Responses to Pain Stimuli

The group-level cerebral responses to electrical stimulation are depicted in Figure 2. The time-domain of EEG analysis revealed that electrical stimuli elicited evoked potentials characterized by N2 and P2 waves at latencies around 148 and 255 ms, respectively. The group-level waveforms and scalp topographies of N2 and P2 waves in the time domain were maximal at the vertex (Figure 2A). The N2 wave demonstrated an extension towards the temporal regions bilaterally, whereas the P2 wave exhibited a more focal scalp topography.

A comparative analysis of peak amplitudes and latencies for these responses under varying stimulus conditions is illustrated in Figure 2B. Findings indicated no significant latency variation in either N2 or P2 waves between high- and low-pain stimuli. However, amplitudes of the brain response either increased (P2) or decreased (N2) with increasing stimulus intensity (P2: t = −3.07, p = 0.0054; N2: t = 4.10, p = 0.0044).

The time-frequency of EEG analysis found that electrical stimuli elicited not only the increase of neuronal oscillations at the gamma band (70–90 hz) between 100 and 300 ms but also the decrease of neuronal oscillations at the alpha band (8–13 hz) between 400 and 800 ms (Figure 2C). We found amplitudes of the brain response either increased (γ-ERS) or decreased (α-ERD) with increasing stimulus intensity (α-ERD: t = −2.69.19, p = 0.013, γ-ERS: t = 3.24, p = 0.0036).

https://doi.org/10.2147/JPR.S477658

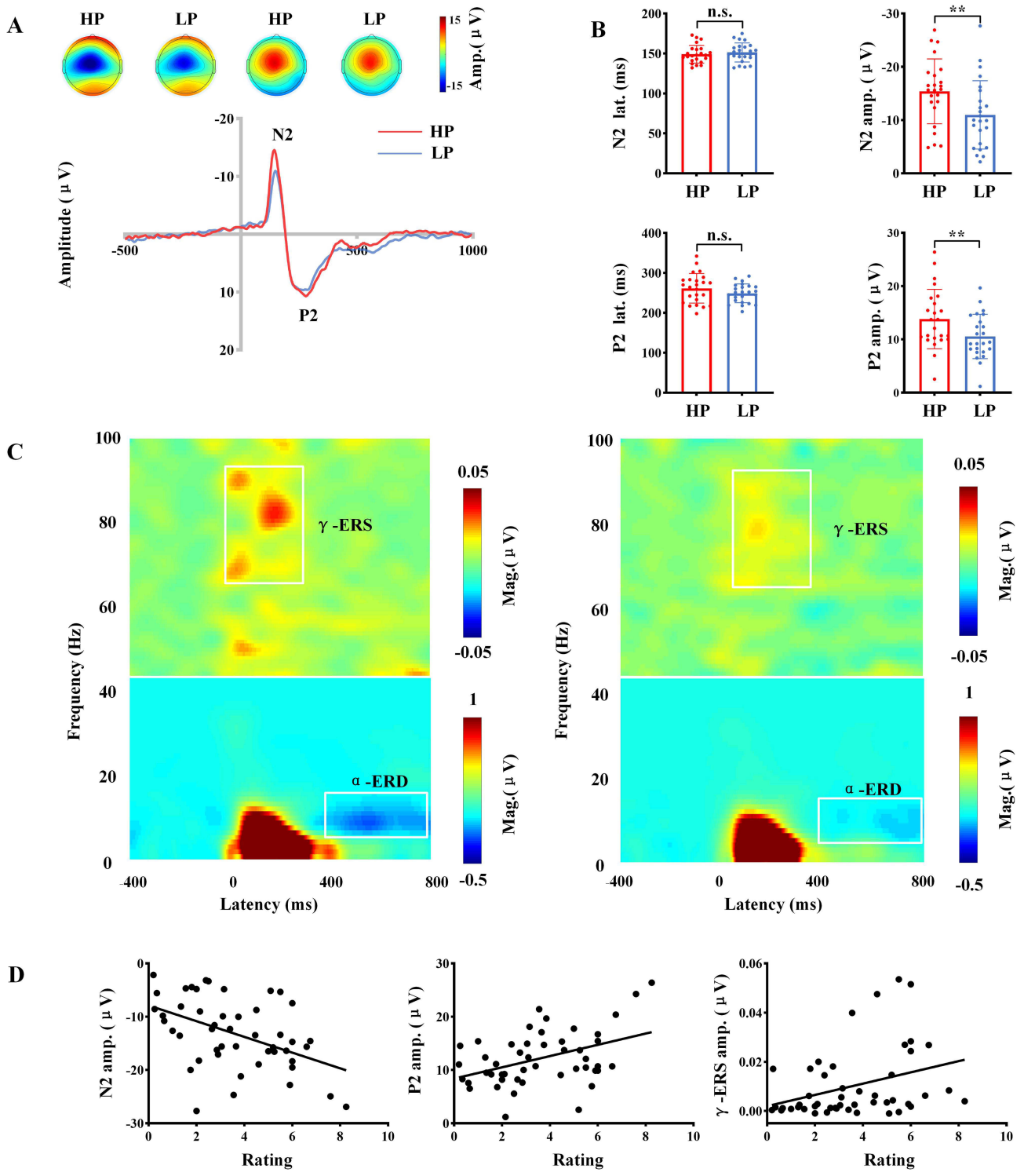

Figure 2 Brain responses evoked by electrical stimuli. (**A**) Group-level waveforms and scalp topographies (1–30 hz). The depicted waveforms were recorded from the vertex (Cz) and color-coded according to stimulus intensity (LS: low stimuli, HS: high stimuli). Topographies show neuronal activity over the scalp. (**B**) Comparisons of N2 and P2 amplitudes and latencies at various stimulus intensities and durations. The error bar reflects the standard error of the measurement (SEM). n.s.: not significant; **: $p < 0.01$. (**C**) Event-related modulations of neural oscillations elicited by electrical stimuli. The time-frequency results for high and low stimuli are shown in the left and right panels, respectively. (**D**) Correlations between subjective ratings of pain perception and brain responses evoked by electrical stimuli.

https://doi.org/10.2147/JPR.S477658

The results of the correlation analysis showed that the subjective ratings of pain were correlated with N2 ($r = -0.46$, $p < 0.001$), P2 ($r = 0.42$, $p = 0.0024$), and γ-ERS ($r = 0.33$, $p = 0.03$), respectively (Figure 2D). No significant relationship between perceived intensity and α-ERD was found.

EMG Responses to Pain Stimuli

To investigate the influence of stimulus intensity on EMG responses, we compared EMG responses between two stimulus conditions (Figure 3A). As can be seen from Table 1, high-intensity electrical stimulation increased the EMG response more than that from low-intensity electrical stimulation. Additionally, significant correlations were found between pain ratings and some electromyography features, including the CS log, CS var, LL log, and ZM var (Figure 3B).

GLM Analysis

As shown in Table 2, the GLM analysis revealed that the EEG features, which displayed notable disparities between high-pain and low-pain stimuli, had an impact on the variation in pain rating. Specifically, the EEG responses of N2 and P2 significantly contributed to the variance in pain rating. For EMG features, only ZM_var significantly contributed to the variance in pain rating. For the combined features from EEG and EMG (N2, P2, and ZM_var), the weights of the EEG response of N2 ($p = 0.039$) and the EMG response of ZM_var ($p = 0.045$) were significant.

Discussion

The objective assessment of pain, particularly in contexts where self-reporting is unfeasible (as in cases of cognitive decline or language deficits), has garnered substantial interest in both experimental and clinical research. In our study, EEG and facial EMG signals were simultaneously recorded from healthy participants to investigate the relationship between physiological signals and perceived pain intensity, as well as to provide an objective and multidimensional approach to pain assessment. The findings revealed that, alongside EEG event-related responses closely correlating with individual pain intensities, facial EMG signals significantly contributed to variations in individual pain perception. The general linear model results indicated that both N2-P2 complex waveforms and the facial myoelectric responses of the zygomatic muscle significantly contributed to variations in pain ratings. This study addresses a significant gap in pain measurement research by providing concrete evidence that facial EMG offers specific insights into pain states and that integrating multidimensional signals enhances pain assessment.

Regarding pain-evoked potentials, our findings indicated that the N2–P2 waves are influenced by stimulus intensity and have a relationship with an individual's pain rating. Previous studies showed reproducible findings that the magnitude of perceived pain was strongly correlated with the magnitude of the pain-evoked N2–P2 response from various modes of nociceptive stimuli, including electrical,[38] nociceptive laser,[31] and mechanical stimulations.[39] Consistent with these studies, our study observed that event-related potentials were associated with the variability of pain perception. In addition, gamma-band oscillations, which are activated by pain, showed a close relationship with individual differences in pain perception. Studies have indicated that pain-induced gamma responses may originate from the somatosensory cortices.[40,41] Gamma oscillations have been suggested to represent the localized processing of sensory, motor, or cognitive information.[42]

It should be pointed out that pain is a multidimensional and complex experience. The analysis of our GLM analysis underscored that the EMG responses of the zygomaticus muscle had a substantial impact on the degree of pain. This suggested that facial EMG signals have the potential to provide pain descriptions that are not sufficiently captured by EEG signals. Facial expressions are a critical medium for pain communication, with significant implications for social interactions, clinical decision-making, and daily pain management.[19,43] Researchers have noted that facial expressions of pain comprise specific muscle movements. For example, one study summarized that pain contained in facial expression arises from a limited set of facial actions, notably those produced by the corrugator, orbicularis oculi, and levator muscles.[44] Patrick et al[45] investigated reactions to pain caused by electric shock and observed a significant increase in brow lowering related to increasing pain. In summary, numerous studies give clear evidence that pain induces changes in variability in the coactivation of action units, and the type of facial responses being displayed during pain is unaffected by the cognitive status of the individual.[44] Presently, the main area of research is centered on facial expressions, whereas

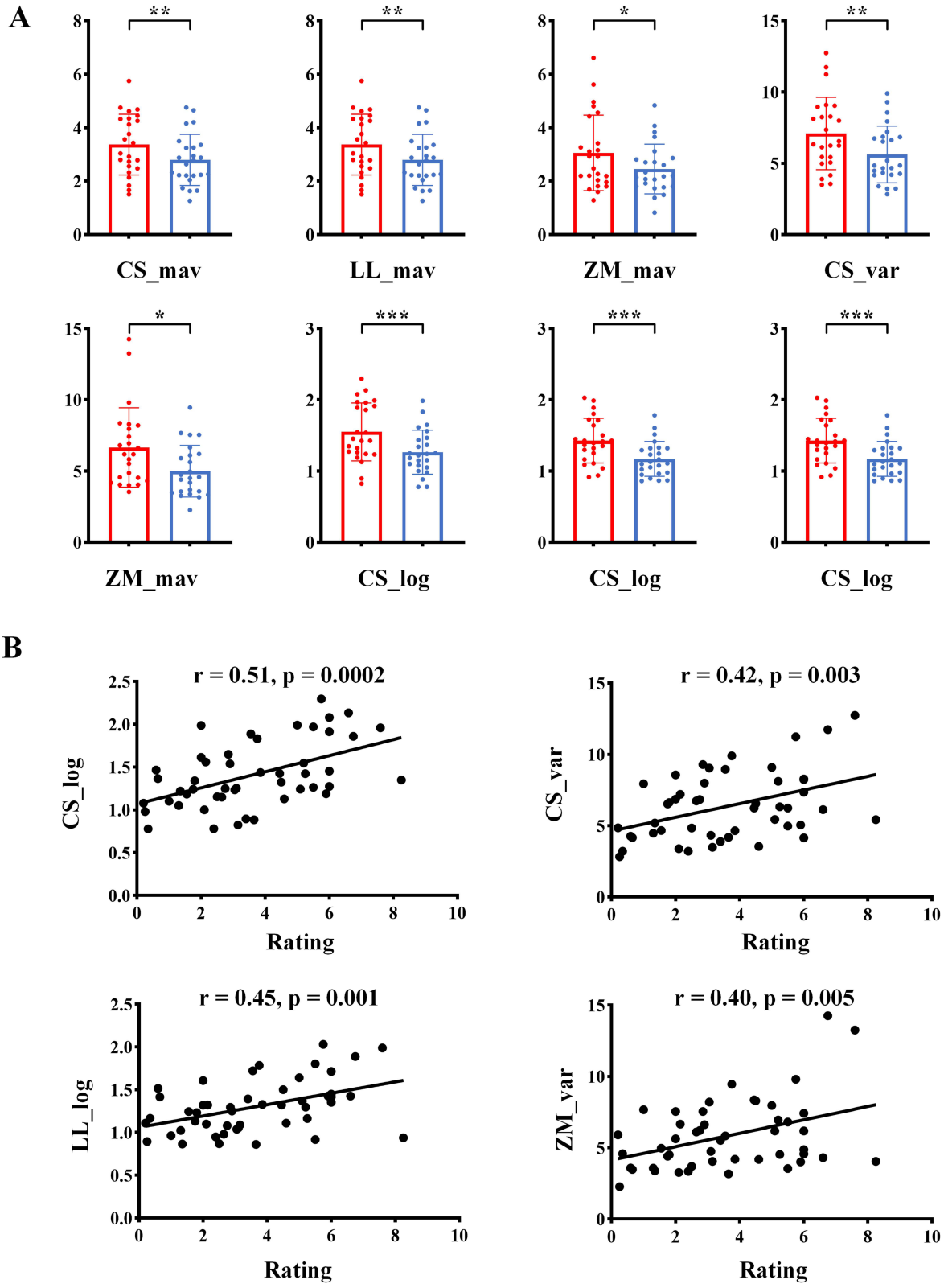

Figure 3 Facial EMG features evoked by electrical stimuli. (**A**) Comparisons of EMG features at various stimulus intensities. The error bar reflects the standard error of the measurement (SEM). n.s.: not significant; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$. (**B**) Correlations between subjective ratings of pain perception and EMG responses evoked by electrical stimuli.

https://doi.org/10.2147/JPR.S477658

Table 1 Comparisons Between Low- and High-Pain Electromyography Features

parameters	high pain	low pain	t	p
CS_mav	3.367 ± 0.263	2.792 ± 0.186	−3.667	0.000
LL_mav	3.067 ± 0.316	2.471 ± 0.188	−3.541	0.000
ZM_mav	3.054 ± 0.408	2.455 ± 0.177	−2.592	0.002
CS_var	7.097 ± 1.316	5.620 ± 0.808	−3.331	0.000
ZM_var	6.655 ± 1.581	4.997 ± 0.669	−2.802	0.001
CS_log	1.550 ± 0.034	1.265 ± 0.019	−5.206	0.000
LL_log	1.427 ± 0.02	1.171 ± 0.012	−6.146	0.000
ZM_log	1.416 ± 0.033	1.157 ± 0.015	−4.352	0.000

Notes: Paired-sample *t*-tests were performed for statistical analysis. A false discovery rate (FDR) procedure was adopted to adjust the P values.
Abbreviations: CS, corrugator supercilii; LL, Labialis levator; ZM, zygomaticus.

there is a limited amount of research on facial EMG. Our investigation found that the characteristics of EMG signals have the ability to represent the ratings of subjective pain. Moreover, the EMG variability could provide a unique and independent contribution to pain assessment compared with the EEG.

Recently, multi-modality pain evaluation methods have been proven to be extremely effective.[46] The integration of many physiological signal evaluations from various sources might collectively contribute to the overall experience of pain.[47] Previous research has demonstrated that integrating multiple physiological signals, including facial expressions, EEG, EMG, skin conductance, respiration, and blood pressure, offering a more precise evaluation of pain intensity.[27] Raul et al combined electrodermal activity (EDA), photoplethysmography (PPG), and respiration (RESP) for multimodal acute pain assessment. They found that while all signals are linked to the autonomic nervous system, they are influenced by different factors and suited to varying conditions. Specifically, EDA provides a more direct measure of sympathetic nervous system activity, making it more effective for detecting pain compared to PPG and RESP.[25] In line with these studies, our GLM result found that indicate that combining EEG and EMG leads to more effective pain assessment, suggesting that each modality provide independent contributions and offer complementary benefits. EEG captures the neural processes associated with pain perception and processing, encompassing both top-down and bottom-up mechanisms that involve sensory, attentional, emotional, and cognitive dimensions.[48,49] However, EEG primarily reflects internal neural mechanisms and does not capture peripheral bodily responses, such as facial expressions. In contrast, facial EMG

Table 2 GLM Results

EEG features only N= 48; R^2 = 0.331; Adj R^2 = 0.289; F(3,44) = 7.349; p<0.001	N2 P2 γ-ERS	1.41 −0.5048 −0.08935	0.039* 0.045* 0.09
EMG features only N= 48; R^2 = 0.392; Adj R^2 = 0.351; F(11,36) = 3.145; p=0.007	CS_mav LL_mav ZM_mav CS_var ZM_var CS_log LL_log ZM_log	1.165 1.520 1.500 0.383 0.394 1.972 4.097 3.766	0.171 0.446 0.542 0.137 0.034* 0.232 0.383 0.545
EEG and EMG features N= 48; R^2 = 0.573; Adj R^2 = 0.544; F(11,36) = 4.394; p<0.001	N2 P2 ZM_var	−0.3202 0.7108 2.154	0.28 0.011* 0.018*

Note: *: p < 0.05.
Abbreviations: CS, corrugator supercilii; LL, Labialis levator; ZM, zygomaticus.

https://doi.org/10.2147/JPR.S477658

offers a direct and real-time measurement of facial muscle activity, serving as an external manifestation of emotional states.[50] This provides a more intuitive and easily interpretable means of assessing pain.[30] The multimodal approach leverages both neural and peripheral indicators, resulting in a more comprehensive evaluation of pain perception.

The study has several limitations. Firstly, the sample size was relatively small, and the study only included healthy participants. To enhance the generalizability of the findings, future research should involve larger, more diverse populations, including individuals with chronic pain or cognitive impairments. Secondly, the pain stimulus used in this study was electrical. Future studies should incorporate other types of pain stimuli, such as thermal or mechanical pressures, which more closely mirror natural pain scenarios. Lastly, we did not compare our approach with previous pain assessment studies. The novelty lies in simultaneously recording EEG and facial EMG to evaluate pain perception, a method not widely explored in existing research. Most prior studies have focused on EEG or facial signals individually, with limited literature on combining both for pain assessment, making direct comparisons with existing methods inappropriate.

Conclusion

Our study demonstrates that facial EMG signals provide valuable insights into pain perception, capturing aspects of pain that are not adequately reflected by EEG alone. By integrating EEG and facial EMG, we offer a more comprehensive assessment of pain intensity, which could contribute to more personalized and objective pain management strategies.

Data Sharing Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Funding

This work was supported by National Key R&D Program of China (Grant No. 2021YFB2011500), and Key R & D Program of Shanxi Province (Grant No. 2019SF-160).

Disclosure

The authors report no conflicts of interest in this work.

References

1. Wilcox CE, Mayer AR, Teshiba TM, et al. The subjective experience of pain: an FMRI study of percept-related models and functional connectivity. *Pain Med*. 2015;16(11):2121–2133. doi:10.1111/pme.12785
2. Spisak T, Kincses B, Schlitt F, et al. Pain-free resting-state functional brain connectivity predicts individual pain sensitivity. *Nat Commun*. 2020;11(1):187. doi:10.1038/s41467-019-13785-z
3. Fink R. Pain assessment: the cornerstone to optimal pain management. *Proceedings (Baylor University Medical Center)*. 2000;13(3):236. doi:10.1080/08998280.2000.11927681
4. Gruss S, Geiger M, Werner P, et al. Multi-modal signals for analyzing pain responses to thermal and electrical stimuli. *JoVE*. 2019;146:e59057.
5. Bouajram RH, Sebat CM, Love D, Louie EL, Wilson MD, Duby JJ. Comparison of self-reported and behavioral pain assessment tools in critically ill patients. *J Int Care Med*. 2020;35(5):453–460. doi:10.1177/0885066618757450
6. He S, Renne A, Argandykov D, Convissar D, Lee J. Comparison of an emoji-based visual analog scale with a numeric rating scale for pain assessment. *JAMA*. 2022;328(2):208–209. doi:10.1001/jama.2022.7489
7. Wu F, Mai W, Tang Y, Liu Q, Chen J, Guo Z. Learning spatial-spectral-temporal EEG representations with deep attentive-recurrent-convolutional neural networks for pain intensity assessment. *Neuroscience*. 2022;481:144–155. doi:10.1016/j.neuroscience.2021.11.034
8. Tiemann L, Hohn VD, Ta Dinh S, et al. Distinct patterns of brain activity mediate perceptual and motor and autonomic responses to noxious stimuli. *Nat Commun*. 2018;9(1):4487. doi:10.1038/s41467-018-06875-x
9. Hu L, Valentini E, Zhang Z, Liang M, Iannetti GD. The primary somatosensory cortex contributes to the latest part of the cortical response elicited by nociceptive somatosensory stimuli in humans. *Neuroimage*. 2014;84:383–393. doi:10.1016/j.neuroimage.2013.08.057
10. Mouraux A, Iannetti GD. Nociceptive laser-evoked brain potentials do not reflect nociceptive-specific neural activity. *J Neurophysiol*. 2009;101(6):3258–3269. doi:10.1152/jn.91181.2008
11. Zhou L, Bi Y, Liang M, et al. A modality-specific dysfunction of pain processing in schizophrenia. *Human Brain Mapp*. 2020;41(7):1738–1753. doi:10.1002/hbm.24906
12. Hu L, Iannetti G. Neural indicators of perceptual variability of pain across species. *Proc Natl Acad Sci*. 2019;116(5):1782–1791. doi:10.1073/pnas.1812499116

13. Scheuren R, Duschek S, Schulz A, Sütterlin S, Anton F. Blood pressure and the perception of illusive pain. *Psychophysiology*. 2016;53(8):1282–1291. doi:10.1111/psyp.12658
14. Jafari H, Gholamrezaei A, Franssen M, et al. Can slow deep breathing reduce pain? An experimental study exploring mechanisms. *J Pain*. 2020;21(9–10):1018–1030. doi:10.1016/j.jpain.2019.12.010
15. Umeda M, Okifuji A. Prediction of pain responses to subsequent cold pressor test via baseline heart rate variability in healthy adults. *Eur. J. Pain*. 2022;26(8):1811–1820. doi:10.1002/ejp.2007
16. Charier DJ, Zantour D, Pichot V, et al. Assessing pain using the variation coefficient of pupillary diameter. *J Pain*. 2017;18(11):1346–1353. doi:10.1016/j.jpain.2017.06.006
17. Sheu E, Versloot J, Nader R, Kerr D, Craig KD. Pain in the elderly: validity of facial expression components of observational measures. *Clin J Pain*. 2011;27(7):593–601. doi:10.1097/AJP.0b013e31820f52e1
18. Simon D, Craig KD, Gosselin F, Belin P, Rainville P. Recognition and discrimination of prototypical dynamic expressions of pain and emotions. *Pain®*. 2008;135(1–2):55–64. doi:10.1016/j.pain.2007.05.008
19. Kappesser J. The facial expression of pain in humans considered from a social perspective. *Philos Trans R Soc B*. 2019;374(1785):20190284. doi:10.1098/rstb.2019.0284
20. Mohanta SR, Veer K. Soft computing based comparative model for the classification of facial expression recognition. *Wireless Pers Commun*. 2024;136(4):2573–2594. doi:10.1007/s11277-024-11414-7
21. Prkachin KM. The consistency of facial expressions of pain: a comparison across modalities. *Pain*. 1992;51(3):297–306. doi:10.1016/0304-3959(92)90213-U
22. Prkachin KM, Mercer SR. Pain expression in patients with shoulder pathology: validity, properties and relationship to sickness impact. *Pain*. 1989;39(3):257–265. doi:10.1016/0304-3959(89)90038-9
23. Prkachin KM, Solomon PE. The structure, reliability and validity of pain expression: evidence from patients with shoulder pain. *Pain*. 2008;139(2):267–274. doi:10.1016/j.pain.2008.04.010
24. Cascella M, Schiavo D, Cuomo A, et al. Artificial intelligence for automatic pain assessment: research methods and perspectives. *Pain Res Manag*. 2023;2023:6018736. doi:10.1155/2023/6018736
25. Fernandez Rojas R, Hirachan N, Brown N, et al. Multimodal physiological sensing for the assessment of acute pain. *Front Pain Res*. 2023;4:1150264. doi:10.3389/fpain.2023.1150264
26. Aljebreen W, Ibrahim DM PainMeter: automatic assessment of pain intensity levels from multiple physiological signals using machine learning. IEEE Access. 2024.;
27. Lin Y, Xiao Y, Wang L, et al. Experimental exploration of objective human pain assessment using multimodal sensing signals. *Front Neurosci*. 2022;16:831627. doi:10.3389/fnins.2022.831627
28. Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods*. 2004;134(1):9–21. doi:10.1016/j.jneumeth.2003.10.009
29. Pahuja S, Veer K, Veer K. Recent approaches on classification and feature extraction of EEG signal: a review. *Robotica*. 2022;40(1):77–101. doi:10.1017/S0263574721000382
30. Mieronkoski R, Syrjälä E, Jiang M, et al. Developing a pain intensity prediction model using facial expression: a feasibility study with electromyography. *PLoS One*. 2020;15(7):e0235545. doi:10.1371/journal.pone.0235545
31. Torta D, Liang M, Valentini E, Mouraux A, Iannetti GD. Dishabituation of laser-evoked EEG responses: dissecting the effect of certain and uncertain changes in stimulus spatial location. *Exp Brain Res*. 2012;218(3):361–372. doi:10.1007/s00221-012-3019-6
32. Li J, Yang H, Xiao Y, et al. The analgesic effects and neural oscillatory mechanisms of virtual reality scenes based on distraction and mindfulness strategies in human volunteers. *Br J Anaesth*. 2023;131(6):1082–1092. doi:10.1016/j.bja.2023.09.001
33. Hu L, Mouraux A, Hu Y, Iannetti GD. A novel approach for enhancing the signal-to-noise ratio and detecting automatically event-related potentials (ERPs) in single trials. *Neuroimage*. 2010;50(1):99–111. doi:10.1016/j.neuroimage.2009.12.010
34. Tiemann L, May ES, Postorino M, et al. Differential neurophysiological correlates of bottom-up and top-down modulations of pain. *Pain*. 2015;156(2):289–296. doi:10.1097/01.j.pain.0000460309.94442.44
35. Hudgins B, Parker P, Scott RN. A new strategy for multifunction myoelectric control. *IEEE Trans Biomed Eng*. 1993;40(1):82–94. doi:10.1109/10.204774
36. Park S-H, Lee S-P. EMG pattern recognition based on artificial intelligence techniques. *IEEE Trans Neural Syst Rehabil Eng*. 1998;6(4):400–405. doi:10.1109/86.736154
37. Tkach D, Huang H, Kuiken TA. Study of stability of time-domain features for electromyographic pattern recognition. *J Neuroeng Rehabil*. 2010;7(1):1–13. doi:10.1186/1743-0003-7-21
38. van den Broeke EN, Mouraux A. Enhanced brain responses to C-fiber input in the area of secondary hyperalgesia induced by high-frequency electrical stimulation of the skin. *J Neurophysiol*. 2014;112(9):2059–2066. doi:10.1152/jn.00342.2014
39. van den Broeke EN, Mouraux A. High-frequency electrical stimulation of the human skin induces heterotopical mechanical hyperalgesia, heat hyperalgesia, and enhanced responses to nonnociceptive vibrotactile input. *J Neurophysiol*. 2014;111(8):1564–1573. doi:10.1152/jn.00651.2013
40. Zhang ZG, Hu L, Hung YS, Mouraux A, Iannetti G. Gamma-band oscillations in the primary somatosensory cortex—a direct and obligatory correlate of subjective pain intensity. *J Neurosci*. 2012;32(22):7429–7438. doi:10.1523/JNEUROSCI.5877-11.2012
41. Tan LL, Oswald MJ, Heinl C, et al. Gamma oscillations in somatosensory cortex recruit prefrontal and descending serotonergic pathways in aversion and nociception. *Nat Commun*. 2019;10(1):983. doi:10.1038/s41467-019-08873-z
42. Yue L, Iannetti G, Hu L. The neural origin of nociceptive-induced gamma-band oscillations. *J Neurosci*. 2020;40(17):3478–3490. doi:10.1523/JNEUROSCI.0255-20.2020
43. Dildine TC, Atlas LY. The need for diversity in research on facial expressions of pain. *Pain*. 2019;160(8):1901. doi:10.1097/j.pain.0000000000001593
44. Kunz M, Meixner D, Lautenbacher S. Facial muscle movements encoding pain—a systematic review. *Pain*. 2019;160(3):535–549. doi:10.1097/j.pain.0000000000001424
45. Patrick CJ, Craig KD, Prkachin KM. Observer judgments of acute pain: facial action determinants. *Journal of Personality and Social Psychology*. 1986;50(6):1291. doi:10.1037/0022-3514.50.6.1291

46. Thiam P, Hihn H, Braun DA, Kestler HA, Schwenker F. Multi-modal pain intensity assessment based on physiological signals: a deep learning perspective. *Front Physiol*. 2021;12:720464. doi:10.3389/fphys.2021.720464
47. Egede JO, Song S, Olugbade TA, et al. Emopain challenge 2020: multimodal pain evaluation from facial and bodily expressions. *IEEE*. 2020;849–856.
48. Apkarian AV, Bushnell MC, Treede R-D, Zubieta J-K. Human brain mechanisms of pain perception and regulation in health and disease. *Eur. J. Pain*. 2005;9(4):463–484. doi:10.1016/j.ejpain.2004.11.001
49. Bushnell MC, Čeko M, Low LA. Cognitive and emotional control of pain and its disruption in chronic pain. *Nat Rev Neurosci*. 2013;14 (7):502–511. doi:10.1038/nrn3516
50. Sato W, Murata K, Uraoka Y, Shibata K, Yoshikawa S, Furuta M. Emotional valence sensing using a wearable facial EMG device. *Sci Rep*. 2021;11 (1):5757. doi:10.1038/s41598-021-85163-z