



OPEN

DATA DESCRIPTOR

A comprehensive EEG dataset of laser-evoked potentials for pain research

Xiangyue Zhao^{1,2}, Jingyao Zhou^{1,2}, Libo Zhang¹ , Yun Zhuang³, Haoqing Duan⁴, Shiyu Wei^{1,2}, Suchen Yao^{1,2}, Xuejing Lu^{1,2}, Yanzhi Bi^{1,2} & Li Hu^{1,2}

Understanding the neural mechanisms of pain is key to the development of novel pain diagnostic and treatment strategies. Here, we present a large-scale, comprehensive electroencephalogram (EEG) dataset of laser-evoked potentials (LEPs) from 678 healthy participants. This dataset comprises high-density EEG recordings and single-trial self-reported pain ratings in response to nociceptive laser stimuli of varying intensities (from 2.5 J to 4.5 J) delivered to either the left or right dorsum of the hand, without any physical or psychological interventions. As the largest nociceptive-evoked EEG dataset to date, it can serve as a valuable resource for mechanistic pain studies such as investigating electrophysiological underpinnings of within-individual and between-individual pain variations, for clinical studies such as providing normal values of LEPs to assess the possible lesions of pain pathways, and for methodological innovations in EEG signal processing such as optimizing preprocessing pipelines and developing new analytical tools.

Background & Summary

Pain is a fundamental sensory and emotional experience crucial for survival, but this protective mechanism can become pathological in chronic pain conditions, leading to significant impairment in quality of life¹. Understanding the neural mechanisms of pain is key to the development of novel pain diagnostic and treatment strategies. Noninvasive brain imaging technologies such as electroencephalography (EEG) have led to remarkable advancements in elucidating the cortical processing of pain signals and the interplay between physiological and psychological processes in pain perception^{2,3}. For example, nociceptive-evoked brain potentials like N1, N2, and P2 waves, and neural oscillations like alpha- and gamma-band oscillations have been shown to encode stimulus intensity⁴, spatial information^{5,6}, and subjective pain perception⁷. These responses have also been utilized to build models that accurately predict pain perception at both within and between individuals^{8–10}. In addition to pain perception, nociceptive-evoked EEG responses have also been associated with motor and autonomic responses to pain^{11,12} and could be influenced by various psychological factors like expectation on pain^{13–15}. Crucially, laser-evoked potentials (LEPs) can be used to assess the peripheral and central nervous system lesions of pain pathways¹⁶, thus providing a reliable diagnostic tool in clinical applications¹⁶.

Despite these advancements, the field of pain neuroimaging also faces significant challenges. One key challenge is that pain research is often hindered by small sample sizes. Many findings in this field have been based on sample sizes of fewer than 30 participants. Such small sample sizes can lead to serious problems, including insufficient statistical power, overestimation of effect sizes, and false positive or negative findings^{17–19}. A large-scale EEG dataset can help address these challenges by providing extensive, high-quality data that enhance the precision and scope of scientific research^{20,21}. Furthermore, the promise of personalized pain treatment remains unfulfilled. Identifying neural biomarkers of individual differences in pain perception is a crucial issue, as it would enable precise diagnosis and tailored therapeutic interventions⁹, ultimately improving patient care. However, current research on pain biomarkers is fraught with difficulties. One major challenge is the low predictive performance of existing biomarker candidates, which limits their widespread applications²². In addition to

¹State Laboratory of Cognitive Science and Mental Health, Institute of Psychology, Chinese Academy of Sciences, Beijing, 100101, China. ²Department of Psychology, University of Chinese Academy of Sciences, Beijing, 100049, China. ³Ningbo Rehabilitation Hospital, School of Rehabilitation Medicine, Wenzhou Medical University, Ningbo, Zhejiang Province, 315040, China. ⁴Beijing Key Laboratory of Learning and Cognition and School of Psychology, Capital Normal University, Beijing, 100048, China. ✉e-mail: biyz@psych.ac.cn; huli@psych.ac.cn

Exp.	N	Age	Gender	Study objectives	Main findings
1	26	21.12 ± 1.97	8 M/18 F	Analgesic effects of music	Music reduced pain unpleasantness and P2 amplitudes ²⁹ .
2	29	24.45 ± 2.71	13 M/16 F	Analgesic effects of synchronous combination of VR and TENS	Combination of VR and TENS reduced pain and LEP amplitudes ³⁰ .
3	39	22.70 ± 1.90	16 M/23 F	Mechanism of movement-induced hypoalgesia	Hand-shaking reduced pain and LEP amplitudes ³¹ .
4	30	23.50 ± 2.66	8 M/22 F	Sustained analgesic effects of drumming rhythm	In-phase drumming reduced pain and N2 amplitudes.
5	65	22.83 ± 2.45	33 M/32 F	Acute analgesic effects of drumming rhythm	In-phase drumming reduced pain and N2 amplitudes.
6	95	21.63 ± 1.80	35 M/60 F	Brain responses to nociceptive stimuli	LEP responses encoded pain intensity and stimulus intensity ^{48–51} .
7	142	21.76 ± 4.60	53 M/89 F	Neural indicators of pain perception	LEP responses robustly encode pain discriminability ¹⁰ .
8	223	20.83 ± 2.29	93 M/130 F	Neural indicators of pain perception	LEP responses robustly encode pain discriminability ¹⁰ .
9	29	21.52 ± 1.74	16 M/13 F	Brain responses to concomitant activations of Aδ and C nociceptors	Both Aδ- and C-LEPs can be reliably detected in most participants when using optimal stimulus parameters ⁴ .

Table 1. Overview of study objectives and main findings of each experiment. Note: Age data are presented as mean ± standard deviation. VR, virtual reality; TENS, transcutaneous electrical nerve stimulation; LEP, laser-evoked potentials; C-LEPs, C-fiber laser-evoked potentials.

basic research efforts aimed at uncovering pain mechanisms, scientists may also develop advanced technologies and methodologies, such as machine learning algorithms, to better analyze the complex associations between pain and neural responses, and to construct more reliable pain biomarkers.

Notably, large-scale EEG datasets have already played a pivotal role in advancing neuroscience research, particularly in elucidating neural mechanisms and enhancing disease diagnosis. For instance, the MODMA dataset—which comprises EEG and audio recordings from 108 clinically depressed patients and matched healthy controls²³—has been employed to demonstrate the diagnostic potential of EEG-based methods for depression using diverse analytical techniques^{24,25}. Likewise, Kiessner *et al.* leveraged the TUH-EEG Corpus, which contains clinical EEG data from over 10,000 epilepsy patients²⁶, to show that larger datasets substantially improve the accuracy of pathology decoding from EEG signals, thereby enhancing the effectiveness of machine-learning-based diagnostic models^{27,28}.

Similarly, establishing a comprehensive EEG dataset for pain research helps overcome these challenges and harnesses the potential of big data. To support research in uncovering the neural dynamics underlying pain perception and facilitate the development of more reliable pain biomarkers, we present a comprehensive LEP dataset. Our dataset includes EEG recordings and self-reported pain ratings from 678 healthy participants who received nociceptive laser stimuli of varying intensities (laser power: from 2.5 J to 4.5 J) and at different sites (left- or right-hand dorsum)^{4,10,29–31}. It focuses solely on non-intervention conditions to help provide normal nociceptive-evoked neural responses. Nociceptive laser stimulators, which emit heat radiation pulses, are a preferred method for inducing experimental pain, as they selectively activate nociceptive-specific Aδ and C fiber nerve endings in the superficial layers of the skin, without causing tactile interference³². This large-scale dataset enables the study of fundamental pain processing and provides insights into neural responses to standardized nociceptive stimuli. Potential applications include mechanistic pain studies, such as investigating the electrophysiological underpinnings of within-individual and between-individual pain variations. The dataset also supports methodological innovations in EEG signal processing, including the development of new analytical tools, such as computational models and machine learning algorithms. Beyond basic research, it can serve as a diagnostic tool for providing normal values of LEPs to assess the possible lesions of pain pathways. By deepening our understanding of pain processing, this dataset has the potential to significantly advance pain research, ultimately aiding therapeutic development and improving clinical outcomes.

Methods

Participants. The database comprises a total of 678 participants, distributed across 9 distinct experiments with varying sample sizes: 26 participants in Experiment 1³³, 29 in Experiment 2³⁴, 39 in Experiment 3³⁵, 30 in Experiment 4³⁶, 65 in Experiment 5³⁷, 95 in Experiment 6³⁸, 142 in Experiment 7³⁹, 223 in Experiment 8⁴⁰, and 29 in Experiment 9⁴¹. Demographic information, including age and gender, was collected for each participant (Table 1). None of the participants had a history of psychiatric disorders, drug abuse, neurosurgical interventions, or implantable medical devices. Written informed consent was obtained from all participants, and the experimental procedures were reviewed and approved by the local ethics review committee (Southwest University for Experiments 6 and 9; Institute of Psychology, Chinese Academy of Sciences for Experiments 1, 2, 3, 4, 5, 7, and 8 [H17025, H22032, H17026, H21103]). All procedures were conducted in accordance with the ethical guidelines of the 1964 Declaration of Helsinki and its later amendments. All research data has been consented to by participants, with explicit agreement for public sharing. Data sharing follows the appropriate ethical approval procedures to ensure the privacy of participants is fully protected. Participants received financial compensation for their involvement. Prior to each experiment, participants were instructed to maintain a regular sleep-wake

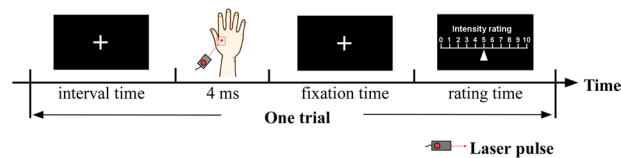


Fig. 1 Trial structure.

cycle and abstain from alcohol or excessive caffeine consumption for at least 24 hours before the experiment. To facilitate rapid EEG setup, participants were asked to refrain from using heavy makeup, facial moisturizers, or hair/scalp products. An overview of the study objectives, main findings, and related publications for each experiment is provided in Table 1.

Demographic information. The demographic information of the participants can be found in the **participants.tsv** file included in the dataset. The data were extracted from paper records and manually entered into the file. Each column in the file is thoroughly explained in the **participants.json** file, which provides detailed definitions of the data elements. Among the participants, the average age of males is 22.00 ± 3.10 years (mean $\pm$ standard deviation [SD]), and the average age of females is 21.48 ± 3.03 years. This meticulous documentation ensures clarity and facilitates further analysis and research.

Data collection design. For all experiments in the dataset, the trial structure was largely consistent (Fig. 1). In each trial, participants were instructed to focus on the laser stimuli, keep their eyes open, and looked at the fixation point displayed on the screen. After each laser stimulation, participants had a few seconds to report their subjective pain intensity using the Numerical Rating Scale (NRS), either verbally or via a computer keypad. The NRS is an 11-point scale ranging from 0 (no pain) to 10 (worst pain imaginable)^{42,43}, with 4 indicating the pinprick pain threshold for most datasets^{44,45}. The next stimulation was then delivered after a random interval. Detailed information for each experiment is presented in Table 2.

Laser stimulation. Nociceptive laser stimuli in all experiments were radiant heat pulses generated by an infrared neodymium yttrium aluminum perovskite (Nd:YAP) laser (Electronical Engineering, Italy). The laser emitted at a wavelength of $1.34 \mu\text{m}$ with a pulse duration of 4 ms⁴⁶. The laser pulse was applied to a pre-defined area on the dorsum of either the left or right hand. The He-Ne laser pulse was transmitted through an optical fiber and focused by lenses to a spot with a diameter of $\sim 7 \text{ mm}$. The laser beam target was manually displaced by at least 1 cm in a random direction to prevent fatigue or sensitization of nociceptors.

EEG data acquisition. The dataset utilized three different types of EEG acquisition devices across various experiments:

Biosemi: For Experiments 1 and 7, EEG was continuously recorded using the ActiveTwo AD-box (BioSemi, Netherlands) at a sampling rate of 1024 Hz from direct current. Participants wore an EEG cap fitted with 62-channel Ag/AgCl electrodes placed according to the international 10–20 system. Electrode impedance was kept below 10 k Ω . The Biosemi system employs a “zero reference” setup, replacing the traditional “ground” electrode with two separate electrodes: a Common Mode Sense active electrode and a Driven Right Leg passive electrode. These electrodes form a feedback loop, driving the participant’s average potential as close as possible to the Analog-to-Digital Converter reference, which is considered the amplifier’s “zero” (for more information, see <https://www.biosemi.com/faq/cms&drl.htm>).

ANT Neuro: In Experiments 2, 4, and 5, we used the ANT Neuro EEG acquisition system (Eenschede, the Netherlands). Participants wore an EEG cap fitted with 32-channel Ag/AgCl electrodes placed according to the international 10–20 system, with a sampling rate set at 1000 Hz. The impedance between the scalp and electrodes was kept below 10 k Ω during acquisition, and CPz was used as the online reference.

Brain Products: In Experiments 3, 6, 8, and 9, EEG data were collected using the Brain Products EEG system (Germany). Participants wore an EEG cap fitted with 64-channel Ag/AgCl electrodes placed according to the international 10–20 system, with a sampling rate set at 1000 Hz. Impedance for all electrodes was maintained below 10 k Ω , with the tip of the nose serving as the reference electrode. Electro-oculographic (EOG) signals were also recorded to monitor eye movements and blinks.

EEG data preprocessing. The preprocessing results are stored in the **derivatives** folder. The Brain Imaging Data Structure (BIDS) data were imported into EEGLAB for merging and electrode localization (the localization files used can be found in the **code-preprocessing_.m** file). The merged and localized data files (*.set) are saved in the **derivatives-session_merged_data** folder. The merged data includes all the raw data collected during the experiments, with some experiments with additional sensory modalities or interventions. However, only the data with nociceptive laser stimuli, either pre-intervention or non-intervention, were extracted for preprocessing and subsequent technical validation. The extracted data underwent high-pass filtering with a cutoff frequency of 1 Hz, low-pass filtering with a cutoff frequency of 100 Hz, and notch filtering from 48 Hz to 52 Hz. EEG epochs were extracted using a time window of 3000 ms (1000 ms before and 2000 ms after stimulus onset), and the baseline was corrected using the pre-stimulus interval ($-1000 \text{ ms} \sim 0 \text{ ms}$). Based on visual inspection, trials contaminated by artifacts due to gross movements were removed (manual removal numbers are recorded in the **CSV-preprocessing.csv** file). Additionally, trials contaminated by eye blinks and movements were corrected

Exp.	EEG device	Stimulated hand	Laser power (J)	Stimulated area (cm ²)	Block numbers	Trial numbers / block	Inter-trial interval (s)	Fixation time (s)	Rating time (s)
1	BioSemi	Left	7 out of 10	4 π	1	16	1–3	3–5	3–5
2	ANT	Left	4 out of 10 for low pain; 7 out of 10 for high pain	5 $\times$ 5	4	40	6–8	3	5
3	BP	Left	7 out of 10	4 π	1	10	7	5	5
4	ANT	Right	7 out of 10	4 π	1	30	2–4	3	5
5	ANT	Right	7 out of 10	4 π	1	30	2–4	3	5
6	BP	Both	2.25/3/3.75/4.5; 2.5/3/3.5/4; 2/2.5/3/3.5	2 $\times$ 3	6	12–14	4.75–6.75	3–5	3.5
7	BioSemi	Left	3/3.5; 3.5/4	5 $\times$ 5	3	10	4–6	3	5
8	BP	Left	3/3.5; 3.5/4	5 $\times$ 5	3	10	4–6	3	5
9	BP	Left (Right for sub013)	1/1.25/1.5/1.75/2/2.25/2.5/2.75/3/3.25/3.5/3.75/4/4.25/4.5	2 $\times$ 3	2	60–75	2–7	3–6	5

Table 2. Experimental parameters for each experiment. Note: “4 out of 10” or “7 out of 10” in the Laser power column refer to the laser stimulus intensity set at the level where participants reported an NRS score of 4 or 7. Fixation time refers to fixation time after pain stimulation.

A comprehensive EEG dataset for Laser-Evoked Potentials for Pain Research

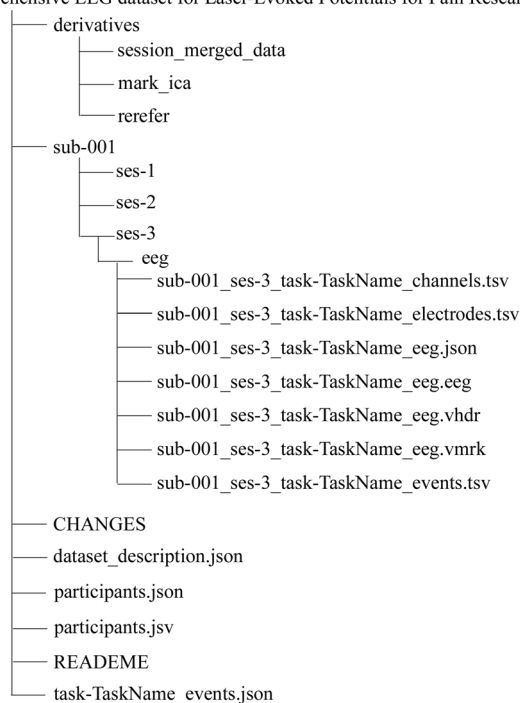


Fig. 2 BIDS data structure.

using the independent component analysis (ICA) algorithm “runica” in EEGLAB⁴⁷. We kept the data file that marked the ICA component to be removed in the **derivatives-mark_ica** folder. To clearly display time-domain LEP responses, low-pass filtering at 30 Hz was applied. Re-referencing was performed using the average reference across the whole brain, with the re-referenced data files stored in the **derivatives-rerefer** folder.

Data Records

The main database contains the raw data from all experiments and is made available in accordance with the BIDS standards (Fig. 2). The dataset can be accessed directly at:

[Experiment1³³: <https://doi.org/10.18112/openneuro.ds005284.v1.0.0>;
 Experiment2³⁴: <https://doi.org/10.18112/openneuro.ds005285.v1.0.0>;
 Experiment3³⁵: <https://doi.org/10.18112/openneuro.ds005289.v1.0.0>;
 Experiment4³⁶: <https://doi.org/10.18112/openneuro.ds005286.v1.0.0>;
 Experiment5³⁷: <https://doi.org/10.18112/openneuro.ds005291.v1.0.0>;
 Experiment6³⁸: <https://doi.org/10.18112/openneuro.ds005293.v1.0.0>;
 Experiment7³⁹: <https://doi.org/10.18112/openneuro.ds005292.v1.0.0>;
 Experiment8⁴⁰: <https://doi.org/10.18112/openneuro.ds005280.v1.0.0>;
 Experiment9⁴¹: <https://doi.org/10.18112/openneuro.ds005473.v1.0.0>].

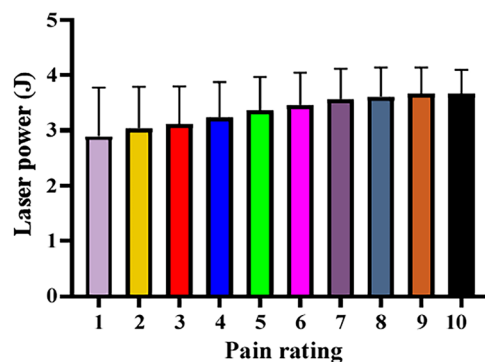


Fig. 3 The relationship between stimulus intensities and pain ratings.

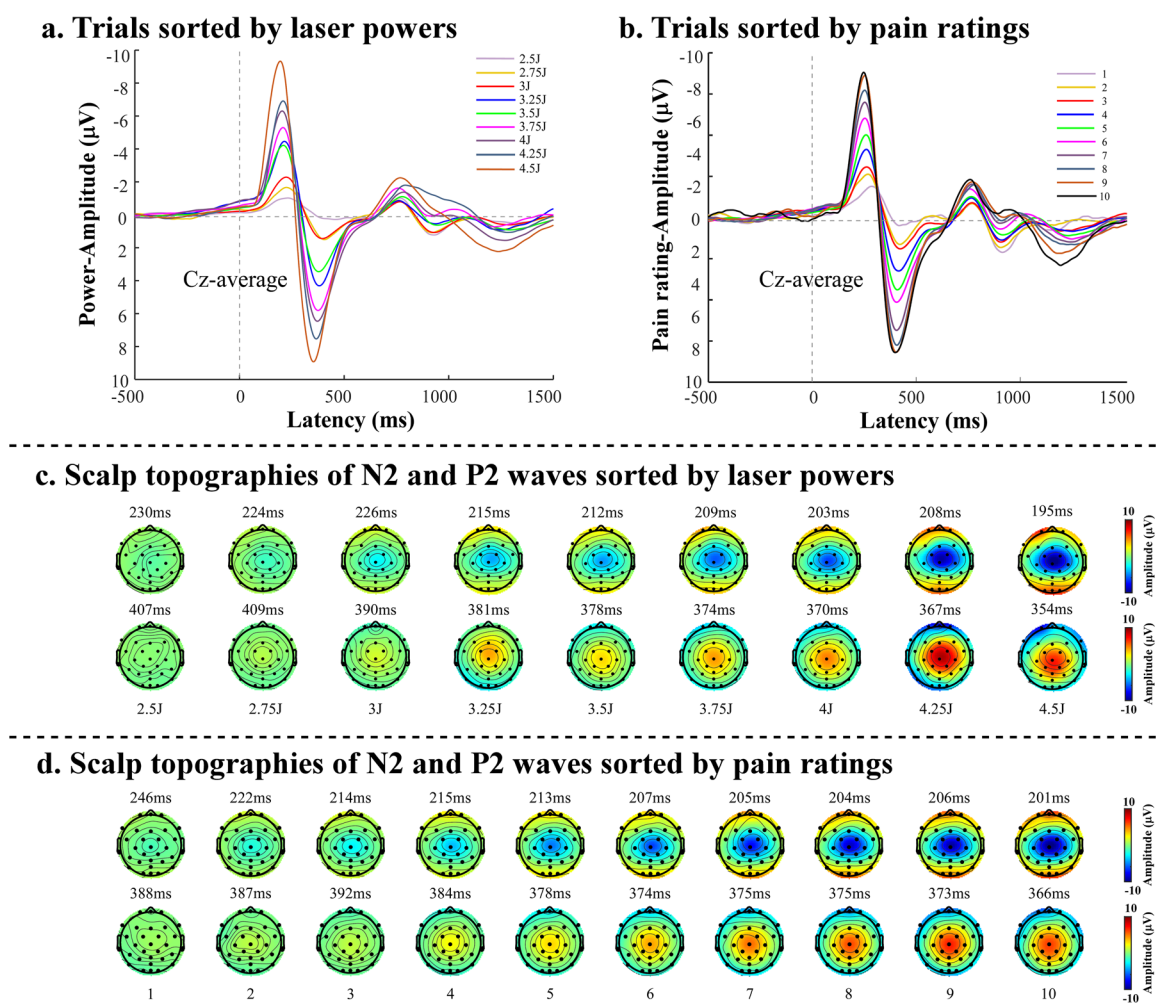


Fig. 4 Technical validations. (a) The average LEP responses at the Cz electrode for different stimulus intensities (2.5 J to 4.5 J). Each curve represents the average response for a specific stimulus intensity, highlighting variations in peak amplitudes and latencies. (b) The average LEP responses at the Cz electrode for different pain ratings (1 to 10), with each line color representing a specific pain rating. The results illustrate how EEG responses change with increasing ratings of perceived pain. (c) Scalp topographies of N2 and P2 waves for different stimulus intensities. (d) Scalp topographies of N2 and P2 waves for different ratings of perceived pain. The timestamp on each map indicates the peak latency of N2 or P2 wave.

Additionally, preprocessed data and the corresponding MATLAB codes are included in the dataset, which can be accessed directly at: <https://github.com/XiangyueZhao/Supplement-Data>.

All experimental information is stored within the dataset. The **dataset_description.json** file provides details on the experiment names, authors, licenses, and indexing information. The **README** file includes an

introduction to each experiment, descriptions of the experimental procedures, participant information, and additional details. The **task-xxx_events.json** files contain detailed descriptions of the condition types for each experiment, along with the time units used for event recording.

Single trial behavioral data. During the preprocessing process, the stimulus intensity and subjective rating of pain perception for each single trial were recorded in each participant's **.set** file. When the data is opened in EEGLAB, these values can be found in the **EEG.epoch** structure.

EEG data. All data are named according to the experiments and identified as follows: 26_ByBiosemi, 29_ByANT, 39_ByBP, 30_ByANT, 65_ByANT, 95_ByBP, 142_ByBiosemi, 223_ByBP, and 29_ByBP. The raw data are organized by subject participation and named as sub-xxx (where xxx is the subject number, starting from 001). For each subject, data are arranged by session and include original EEG data files (formats: **_eeg.eeg/_eeg.bdf**), along with the associated **_channels.tsv**, **_electrodes.tsv**, **_events.tsv**, and **_eeg.json** files. The **_channels.tsv** file contains the names, types, and units of electrode channels; the **_electrodes.tsv** file contains the electrode positions; the **_events.tsv** file records the start and duration of each event, the sampling rate, and the type of markers; the **_eeg.json** file provides details on the data collection institution, address, department, equipment used, EEG reference electrode, project name, number of electrodes, sampling type, sampling time, and sampling frequency.

Technical Validation

Our technical validation includes quality control of behavioral data and EEG responses to nociceptive laser stimuli. The relationship between stimulus intensities (in unit of Joule [J]) and pain ratings is illustrated in Fig. 3, showing an increasing trend of higher pain ratings corresponding to higher stimulus intensities. These behavioral patterns offer valuable insights into how varying stimulus intensities influence subjective pain perception, supporting the validity of graded laser stimulus intensities in eliciting graded pain perception.

For the EEG data, we calculated LEP responses for each stimulus intensity (Fig. 4, the code and the **.mat** data file are available in the **supplement** folder, directly accessible at: <https://github.com/XiangyueZhao/Supplement-Data>). As expected, LEP responses remarkably increased with stimulus intensities of nociceptive laser stimuli. A similar relationship was observed between LEP responses and subjective pain ratings, confirming the strong relationship among nociceptive stimulus intensities, subjective pain ratings, and LEP responses in our dataset.

Data availability

All research data has been consented to by participants, with explicit agreement for public sharing. Data sharing follows the appropriate ethical approval procedures to ensure the privacy of participants is fully protected.

Code availability

The latest versions of all related codes are available in this repository: [<https://github.com/XiangyueZhao/Supplement-Data>].

Received: 5 February 2025; Accepted: 28 August 2025;

Published online: 02 September 2025

References

- Moriarty, O., McGuire, B. E. & Finn, D. P. The effect of pain on cognitive function: a review of clinical and preclinical research. *Progress in neurobiology* **93**, 385–404, <https://doi.org/10.1016/j.pneurobio.2011.01.002> (2011).
- Malfliet, A. *et al.* Brain changes associated with cognitive and emotional factors in chronic pain: A systematic review. *European journal of pain* **21**, 769–786, <https://doi.org/10.1002/ejp.1003> (2017).
- Nicholas, M. K. The biopsychosocial model of pain 40 years on: time for a reappraisal? *Pain* **163**, S3–s14, <https://doi.org/10.1097/j.pain.0000000000002654> (2022).
- Hu, L., Cai, M. M., Xiao, P., Luo, F. & Iannetti, G. D. Human brain responses to concomitant stimulation of A δ and C nociceptors. *The Journal of neuroscience* **34**, 11439–11451, <https://doi.org/10.1523/jneurosci.1355-14.2014> (2014).
- Valentini, E. *et al.* The primary somatosensory cortex largely contributes to the early part of the cortical response elicited by nociceptive stimuli. *NeuroImage* **59**, 1571–1581, <https://doi.org/10.1016/j.neuroimage.2011.08.069> (2012).
- Hu, L., Valentini, E., Zhang, Z. G., Liang, M. & Iannetti, G. D. The primary somatosensory cortex contributes to the latest part of the cortical response elicited by nociceptive somatosensory stimuli in humans. *NeuroImage* **84**, 383–393, <https://doi.org/10.1016/j.neuroimage.2013.08.057> (2014).
- Zhang, Z. G., Hu, L., Hung, Y. S., Mouraux, A. & Iannetti, G. D. Gamma-band oscillations in the primary somatosensory cortex—a direct and obligatory correlate of subjective pain intensity. *The Journal of neuroscience* **32**, 7429–7438, <https://doi.org/10.1523/jneurosci.5877-11.2012> (2012).
- Huang, G. *et al.* A novel approach to predict subjective pain perception from single-trial laser-evoked potentials. *NeuroImage* **81**, 283–293, <https://doi.org/10.1016/j.neuroimage.2013.05.017> (2013).
- Hu, L. & Iannetti, G. D. Neural indicators of perceptual variability of pain across species. *Proceeding of the national academy of sciences of the united states of America* **116**, 1782–1791, <https://doi.org/10.1073/pnas.1812499116> (2019).
- Zhang, L. B. *et al.* Selective and replicable neuroimaging-based indicators of pain discriminability. *Cell reports medicine* **3**, 100846, <https://doi.org/10.1016/j.xcrm.2022.100846> (2022).
- Schulz, E., Tiemann, L., Witkovsky, V., Schmidt, P. & Ploner, M. Oscillations are involved in the sensorimotor transformation of pain. *Journal of neurophysiology* **108**, 1025–1031, <https://doi.org/10.1152/jn.00186.2012> (2012).
- Tiemann, L. *et al.* Distinct patterns of brain activity mediate perceptual and motor and autonomic responses to noxious stimuli. *Nature communications* **9**, 4487, <https://doi.org/10.1038/s41467-018-06875-x> (2018).
- Bott, F. S. *et al.* Local brain oscillations and interregional connectivity differentially serve sensory and expectation effects on pain. *Science advances* **9**, eadd7572, <https://doi.org/10.1126/sciadv.add7572> (2023).
- Nickel, M. M. *et al.* Temporal-spectral signaling of sensory information and expectations in the cerebral processing of pain. *Proceedings of the national academy of sciences of the united states of America* **119**, <https://doi.org/10.1073/pnas.2116616119> (2022).

15. Strube, A., Rose, M., Fazeli, S. & Büchel, C. The temporal and spectral characteristics of expectations and prediction errors in pain and thermoception. *eLife* **10**, <https://doi.org/10.7554/eLife.62809> (2021).
16. Treede, R. D. Neurophysiological studies of pain pathways in peripheral and central nervous system disorders. *Journal of neurology* **250**, 1152–1161, <https://doi.org/10.1007/s00415-003-0237-7> (2003).
17. Button, K. S. *et al.* Power failure: why small sample size undermines the reliability of neuroscience. *Nature reviews neuroscience* **14**, 365–376, <https://doi.org/10.1038/nrn3475> (2013).
18. Christley, R. M. Power and Error: Increased Risk of False Positive Results in Underpowered Studies. *The open epidemiology journal* **3**, 16–19, <https://doi.org/10.2174/1874297101003010016> (2010).
19. Ioannidis, J. P. Why most published research findings are false. *PLoS medicine* **2**, e124, <https://doi.org/10.1371/journal.pmed.0020124> (2005).
20. Gram, M., Graversen, C., Olesen, S. S. & Drewes, A. M. Dynamic spectral indices of the electroencephalogram provide new insights into tonic pain. *Clinical neurophysiology* **126**, 763–771, <https://doi.org/10.1016/j.clinph.2014.07.027> (2015).
21. Schulz, E., Zherdin, A., Tiemann, L., Plant, C. & Ploner, M. Decoding an individual's sensitivity to pain from the multivariate analysis of EEG data. *Cerebral cortex* **22**, 1118–1123, <https://doi.org/10.1093/cercor/bhr186> (2012).
22. Zhang, L. B. *et al.* Advances and challenges in neuroimaging-based pain biomarkers. *Cell reports medicine* **5**, 101784, <https://doi.org/10.1016/j.xcrm.2024.101784> (2024).
23. Cai, H. *et al.* A multi-modal open dataset for mental-disorder analysis. *Scientific data* **9**, 178, <https://doi.org/10.1038/s41597-022-01211-x> (2022).
24. Ksibi, A. *et al.* Electroencephalography-Based Depression Detection Using Multiple Machine Learning Techniques. *Diagnostics* **13**, <https://doi.org/10.3390/diagnostics13101779> (2023).
25. Wang, Z., Hu, C., Liu, W., Zhou, X. & Zhao, X. EEG-based high-performance depression state recognition. *Frontiers in neuroscience* **17**, 1301214, <https://doi.org/10.3389/fnins.2023.1301214> (2023).
26. Obeid, I. & Picone, J. The Temple University Hospital EEG Data Corpus. *Frontiers in neuroscience* **10**, 196, <https://doi.org/10.3389/fnins.2016.00196> (2016).
27. Kiessner, A. K., Schirrmeister, R. T., Gemein, L. A. W., Boedercker, J. & Ball, T. An extended clinical EEG dataset with 15,300 automatically labelled recordings for pathology decoding. *NeuroImage: clinical* **39**, 103482, <https://doi.org/10.1016/j.nicl.2023.103482> (2023).
28. Kiessner, A. K., Schirrmeister, R. T., Boedercker, J. & Ball, T. Reaching the ceiling? Empirical scaling behaviour for deep EEG pathology classification. *Computers in biology and medicine* **178**, 108681, <https://doi.org/10.1016/j.combiomed.2024.108681> (2024).
29. Lu, X., Thompson, W. F., Zhang, L. & Hu, L. Music Reduces Pain Unpleasantness: Evidence from an EEG Study. *Journal of pain research* **12**, 3331–3342, <https://doi.org/10.2147/jpr.S212080> (2019).
30. Bi, Y. *et al.* Enhancing pain modulation: the efficacy of synchronous combination of virtual reality and transcutaneous electrical nerve stimulation. *General psychiatry* **36**, e101164, <https://doi.org/10.1136/gpsych-2023-101164> (2023).
31. Lu, X., Yao, X., Thompson, W. F. & Hu, L. Movement-induced hypoalgesia: behavioral characteristics and neural mechanisms. *Annals of the new york academy of sciences* **1497**, 39–56, <https://doi.org/10.1111/nyas.14587> (2021).
32. Treede, R. D., Kief, S., Hölzer, T. & Bromm, B. Late somatosensory evoked cerebral potentials in response to cutaneous heat stimuli. *Electroencephalography and clinical neurophysiology* **70**, 429–441, [https://doi.org/10.1016/0013-4694\(88\)90020-x](https://doi.org/10.1016/0013-4694(88)90020-x) (1988).
33. Xiangyue, Z. *et al.* 26 By Biosemi. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005284.v1.0.0> (2024).
34. Xiangyue, Z. *et al.* 29 By ANT. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005285.v1.0.0> (2024).
35. Xiangyue, Z. *et al.* 39 By BP. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005289.v1.0.0> (2024).
36. Xiangyue, Z. *et al.* 30 By ANT. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005286.v1.0.0> (2024).
37. Xiangyue, Z. *et al.* 65 By ANT. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005291.v1.0.0> (2024).
38. Xiangyue, Z. *et al.* 95 By BP. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005293.v1.0.0> (2024).
39. Xiangyue, Z. *et al.* 142 By Biosemi. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005292.v1.0.0> (2024).
40. Xiangyue, Z. *et al.* 223 By BP. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005280.v1.0.0> (2024).
41. Xiangyue, Z. *et al.* 29 By BP. *OpenNeuro*. [Dataset] <https://doi.org/10.18112/openneuro.ds005473.v1.0.0> (2024).
42. Ferreira-Valente, M. A., Pais-Ribeiro, J. L. & Jensen, M. P. Validity of four pain intensity rating scales. *Pain* **152**, 2399–2404, <https://doi.org/10.1016/j.pain.2011.07.005> (2011).
43. Karcioglu, O., Topacoglu, H., Dikme, O. & Dikme, O. A systematic review of the pain scales in adults: Which to use? *The American journal of emergency medicine* **36**, 707–714, <https://doi.org/10.1016/j.ajem.2018.01.008> (2018).
44. Clark, J. A., Brown, C. A., Jones, A. K. & El-Dereby, W. Dissociating nociceptive modulation by the duration of pain anticipation from unpredictability in the timing of pain. *Clinical neurophysiology* **119**, 2870–2878, <https://doi.org/10.1016/j.clinph.2008.09.022> (2008).
45. Granovsky, Y., Granot, M., Nir, R. R. & Yarnitsky, D. Objective correlate of subjective pain perception by contact heat-evoked potentials. *The journal of pain* **9**, 53–63, <https://doi.org/10.1016/j.jpain.2007.08.010> (2008).
46. Iannetti, G. D. *et al.* Evidence of a specific spinal pathway for the sense of warmth in humans. *Journal of neurophysiology* **89**, 562–570, <https://doi.org/10.1152/jn.00393.2002> (2003).
47. Delorme, A. & Makeig, S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of neuroscience methods* **134**, 9–21, <https://doi.org/10.1016/j.jneumeth.2003.10.009> (2004).
48. Jin, Q. Q. *et al.* Somatotopic Representation of Second Pain in the Primary Somatosensory Cortex of Humans and Rodents. *The Journal of neuroscience* **38**, 5538–5550, <https://doi.org/10.1523/jneurosci.3654-17.2018> (2018).
49. Zhang, H., Lu, X., Bi, Y. & Hu, L. A modality selective effect of functional laterality in pain detection sensitivity. *Scientific reports* **11**, 6883, <https://doi.org/10.1038/s41598-021-85111-x> (2021).
50. Yue, L. *et al.* Neuronal mechanisms of nociceptive-evoked gamma-band oscillations in rodents. *Neuron*, <https://doi.org/10.1016/j.neuron.2024.12.011> (2025).
51. Liu, X., Wei, S., Zhao, X., Bi, Y. & Hu, L. Establishing the relationship between subjective perception and neural responses: Insights from correlation analysis and representational similarity analysis. *NeuroImage* **295**, 120650, <https://doi.org/10.1016/j.neuroimage.2024.120650> (2024).

Acknowledgements

This work was supported by the Beijing Natural Science Foundation (JQ22018, 5252019), National Key Research and Development Program of China (2023YFC2508702), and National Natural Science Foundation of China (32071061).

Author contributions

Xiangyue Zhao, Jingyao Zhou, Libo Zhang, Yun Zhuang, Xuejing Lu, Yanzhi Bi, and Li Hu conceived and conducted this research, and drafted the manuscript. Haoqing Duan, Shiyu Wei, and Suchen Yao provided support for data processing.

Competing interests

The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to Y.B. or L.H.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2025