Supplemental Information

Supplemental methods (Experiments 1, 2, 3)

Time-frequency decomposition (TFD)

 A TFD of the EEG signal was obtained using a windowed Fourier transform (WFT) with a fixed 250-ms Hanning window. The WFT yielded, for each EEG epoch, a complex time-frequency 7 estimate $F(t, f)$ at each point (t, f) of the time-frequency plane, extending from -500 to 1,000 ms (in steps of 1 ms) in the time domain, and from 1 to 100 Hz (in steps of 1 Hz) in the 9 frequency domain. The resulting spectrogram, $P(t, f) = |F(t, f)|^2$, represents the signal power as a joint function of time and frequency at each time-frequency point. The spectrograms were baseline-corrected (reference interval: -400 to -100 ms relative to stimulus onset) at each frequency *f* using the *subtraction* approach, which avoids the positive bias introduced by the *percentage* approach (1). This reference interval was chosen to reduce the adverse influence of spectral estimates biased by windowing post-stimulus activity and padding values.

Point-by-point statistical analyses

The point-by-point statistical analyses were composed of the following steps:

Step 1. We tested whether the brain responses both in the time domain and time-frequency

domain within the post-stimulus interval were significantly different from those within the pre-

stimulus interval by performing a bootstrapping test (2). At each time point (*t*) or time-frequency

21 point (t, f) , we extracted a collection of numerical samples from the 96 subjects, and compared

with a similar collection of numerical samples from the baseline interval. The null hypothesis

 was that there was no difference between the means of the two samples, i.e., no difference between the mean magnitude values in pre-stimulus and post-stimulus intervals. The pseudo-t statistic of two populations was calculated, and its probability distribution was estimated by permutation testing (5,000 times). After obtaining the distribution of the pseudo-t statistics from the baseline, we calculated the bootstrap p values for the null hypothesis. This procedure identified the time intervals or time-frequency regions in which the brain responses were significantly different relative to the baseline interval. To account for multiple comparisons across time and frequency, the significance level (expressed as p value) was corrected using an FDR procedure (3).

11 Step 2. To identify time intervals or time-frequency regions whose magnitude reflected the within-subject variability of pain ratings, we performed, in each subject, a point-by-point linear correlation analysis between single-trial magnitudes and the corresponding single-trial ratings of pain perception. The obtained correlation coefficient was transformed to z values using the Fisher r-to-z transformation. z values from all subjects were finally compared against zero using a one-sample t-test.

 Step 3. To identify time intervals or time-frequency regions whose magnitude reflected the between-subject variability of pain ratings, we performed a point-by-point linear correlation analysis between single-subject average magnitudes and the corresponding single-subject average pain ratings.

 Step 4. To account for the multiple comparison problem in the point-by-point analyses described in steps 2 and 3, significant time points or time-frequency pixels were categorized in clusters based on their adjacency in the time domain or time-frequency domain (cluster-level statistical 4 analysis) (4). Specifically, to explore whether the 'y-ERS' region was able to reflect both within-5 subject and between-subject pain variability, we defined a *conjunct* 'y-ERS' cluster based on the following three criteria: (1) the cluster had to show a significant magnitude difference compared to the pre-stimulus interval (this was assessed using the bootstrapping test described in Step 1); (2) the magnitude of the cluster had to show a significant correlation with single-trial pain ratings (this was assessed using the point-by-point within-subject correlation analysis described in Step 2), as well as a significant correlation with single-subject pain ratings (this was assessed using the point-by-point between-subject correlation analysis described in Step 3); (3) only the cluster 12 with the largest number of significant time-frequency pixels in the γ -frequency band (30-100 Hz) was selected to control for false-positive observations (4).

15 Step 5. To confirm the relationship between the magnitude of ' γ -ERS' and pain ratings within 16 conjunct ' γ -ERS' cluster, we randomly permutated 5,000 times the TFDs (5). Within-subject and between-subject correlation analyses were performed at each time-frequency point of each cluster in each permutation, thus yielding two cluster-level statistics (t-values and r-values respectively). Distributions of the cluster-level permutation t-statistics/r-statistics were obtained, and the two- tailed p values were respectively derived by locating the observed t value and r value under the estimated permutation distribution.

1 For display purposes, we measured the magnitudes of γ -ERS' of each trial and subject by 2 computing the top 20% of all time-frequency points within the conjunct γ -ERS' cluster, and showed their correlations with pain ratings at both within-subject and between-subject levels.

Exploring the interactions of within-subject and between-subject effects

 To identify the response features reflecting *within-subject* and *between-subject* pain variability, the 96 single subjects were first sorted by their mean pain intensity ratings across trials. Two subgroups reflecting low-pain and high-pain subjects were defined by median split. Subsequently, single trials of each subject were sorted by reported pain intensity. The first and the last 20 trials, respectively reflecting the low-pain and the high-pain brain responses, were averaged time-locked to stimulus onset. This procedure yielded, in each subject (belonging to either the low-pain or the high-pain subgroup), two average waveforms, one reflecting low-pain trials, and the other reflecting high-pain trials.

 Baseline-to-peak amplitudes of N1, N2, and P2 waves were measured in the two average waveforms of each subject (N1: C4-Fz; N2 and P2: Cz-nose) (6). These amplitude values were compared using a two-way mixed-designed ANOVA, with a within-subject factor 'trial type' (two levels: low-pain trials, high-pain trials) and a between-subject factor 'subject type' (two levels: low-pain subjects, high-pain subjects).

 In the time-frequency domain, baseline corrected TFDs of low-pain and high-pain trials were averaged in each subject, yielding, in each subject, two average TFDs, one reflecting low-pain trials and the other reflecting high-pain trials. According to previous publications (1, 7, 8), the

Describing between-subject pain variability

 To assess the between-subject variability, we used the same data but this time sorted the individuals by their mean self-reported pain ratings across all trials. This analysis gives the relative range of the pain scale each individual used. We then median-split the individuals into high-pain and low-pain subgroups. We found clear differences in the mean ratings of pain sensitivity between subgroups: they were 4.9±0.6 and 6.6±0.5, respectively (Figure S1D).

 We next asked whether neural activity could predict this between-subject variability, as it did in the within-subject analysis. In contrast to the within-subject analysis, we found that variability across different individuals was largely not reflected in the neural responses. Almost all explored features of the EEG responses that accurately reflected subjective pain reports at within-subject level failed to reflect the pain sensitivity across different individuals (Figure S1E&F). The only 23 notable exception was the γ -ERS', whose activity was reliably and significantly larger in the

- high-pain than in the low-pain subjects (Figure S1F). Similar results were obtained when
- subjective pain ratings were tripartite in low-third, middle-third, and high-third subjects.

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 Figure S1. Electrophysiological indicators of within-subject and between-subject variability in pain ratings. *A*: For each subject, trials were sorted by reported pain intensity. Median-split low- pain and high-pain trials (n=20 each) are displayed in blue and orange, respectively. *B*: Time- domain analysis. Group-level LEP waveforms: N2-wave and P2-wave amplitudes are 5 significantly larger in high-pain than in low-pain trials (p<0.001 for both waves; paired-sample t-6 test). C : Time-frequency analysis. Group-level TFDs: Magnitudes of 'LEP', ' α -ERD', and ' γ -ERS' 7 are significantly larger in high-pain than in low-pain trials ($p<0.001$ for all features; paired- sample t-test). Similar results were obtained when pain ratings were tripartite in low-third, middle-third, and high-third trials. *D*: Participants were sorted by their mean self-reported pain ratings across all trials. Median split low-pain and high-pain subjects (n=48 each) are displayed in green and purple, respectively. *E*: Time-domain analysis. Group-level LEPs: N2-wave and P2- wave amplitudes are virtually identical in low-pain and high-pain subjects (p>0.05 for both waves; independent-sample t-test). *F*: Time-frequency analysis. Group-level TFDs: While the 14 magnitudes of 'LEP' and ' α -ERD' are not significantly different between subgroups (p >0.05 for 15 both features; independent-sample t-test), 'γ-ERS' is significantly larger in high-pain than in low- pain subjects (p=0.01; independent-sample t-test). Similar results were obtained when subjective pain ratings were tripartite in low-third, middle-third, and high-third subjects.

 Figure S2. Within-subject and between-subject variability in perception of auditory, visual, and 4 non-nociceptive somatosensory stimuli. A, C, E: For each subject, trials were sorted by perceived intensity ratings. *B, D, F*: Participants were sorted by their mean perceived intensity ratings across all trials.

t value

r value

A: Permutation tests within γ -ERS cluster of nociceptive responses

1 2 Latency (ms)

Figure S3. Relationship between subjective intensity ratings and 'y-ERS' elicited by nociceptive 4 and non-nociceptive somatosensory stimuli. *A*: The 'y-ERS' cluster elicited by nociceptive stimuli reflected both within-subject variability in pain ratings (t-value, vertical red line in the middle plot; p<0.001; 5,000 permutations) and between-subject variability in pain ratings (r-value, vertical red 7 line in the right plot; $p=0.005$; 5,000 permutations). **B**: The 'y-ERS' elicited by non-nociceptive somatosensory stimuli only reflected within-subject perceptual variability (t-value, vertical red line in the middle plot; p<0.001; 5,000 permutations), but not between-subject perceptual 10 variability (r-value, vertical red line in the right plot; p=0.68; 5,000 permutations).

 Figure S4. EOG signals recorded from a subject with particularly strong ocular movements and eye blinks (*A***) and from all subjects (***B***).** Single-trial (*A*) and single-subject (*B*) EOG waveforms in the time domain are coloured and superimposed (first row). Across-trial (*A*) and across-subject (*B*) averages are displayed in black. The time-frequency representation of single trials (*A*) and of single trials from all subjects (*B*) are displayed in the second row. Note the lack 8 of a clear time-locked ' γ -ERS' response. Note also how time-frequency EOG signals did not reflected either within-subject or between-subject variability in pain ratings (third row).

 Figure S5. Comparison of the latency of '-ERS' magnitude and pain-related behavior. 4 Single-subject latencies of γ -ERS' magnitude were significantly shorter than those of pain-related 5 behavior (151 \pm 11 ms vs. 224 \pm 8 ms; p<0.001, paired-sample t test). This result indicates that the 6 early 'y-ERS' recorded in rats does not reflect muscle activity. Data were collected from 5 adult male rats in a new experiment, in which the operating signals of the camera and the onset of the

- laser pulses were sampled synchronously with the EEG data.
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 Figure S6. Receiver operating characteristic (ROC) analysis quantifying the ability of '- ERS' to discriminate between individual human participants with different pain sensitivity. 5 ROC analysis showed that ' γ -ERS' amplitude effectively discriminates individuals participants who provided ratings below vs above the pain threshold (i.e., 4), as well as individual participants who reported low and high (e.g., participants who provided ratings below vs above 7). The graph reports the mean discrimination between all pairs of two individual participants with pain ratings lower than vs. higher than 4, 5, 6, and 7. Discrimination was significantly greater than chance (i.e., 0.5) in all conditions except when discriminating participants with a pain ratings lower vs. higher than 5. Error bars show the standard error across subjects.

 Figure S7. Experiment 1: Prediction of individual pain sensitivity using the 'γ-ERS' response. *A*: Time-frequency distribution (TFD) of the 'γ-ERS' response (180-260 ms, 60-85 Hz) and of its first three PCs (which explained 67.4%, 15.1%, and 8.4% of the variance of 'γ-ERS', respectively). *B*: A random forest regression model based on the first 20 PCs achieved accurate prediction of individual pain sensitivity. Subjects are sorted by reported pain intensity (green). Corresponding predicted pain intensity is superimposed (red). *C*: Importantly, real and predicted pain intensity were highly correlated across subjects (r=0.93, p<0.001; each gray dot represents a single subject).

Table S1. Correlations between subjective ratings of perception intensity and brain responses evoked by auditory, visual, and nonnociceptive somatosensory stimuli. Data from Experiment 2. Significant correlations that survived FDR correction are marked in bold.

	Auditory		Visual		Non-nociceptive somatosensory	
	Within-subject correlation	Between-subject correlation	Within-subject correlation	Between-subject correlation	Within-subject correlation	Within-subject correlation
N1 wave	-0.24 ± 0.18	-0.11 (p=0.27)	-0.44 ± 0.24	-0.08 (p=0.41)	-0.31 ± 0.17	-0.17 (p=0.08)
P ₂ wave	0.20 ± 0.18	0.01 (p=0.93)	0.33 ± 0.20	0.13 (p=0.18)	0.32 ± 0.18	0.04 (p=0.68)
'ERP' magnitude	0.20 ± 0.17	0.07 (p=0.46)	0.34 ± 0.18	0.13 (p=0.19)	0.43 ± 0.17	0.16 (p=0.12)
α -ERD'	-0.04 ± 0.16	-0.002 (p=0.99)	0.02 ± 0.16	0.12 (p=0.24)	0.02 ± 0.16	0.08 (p=0.44)
γ -ERS'	0.02 ± 0.16	-0.06 (p=0.52)	0.01 ± 0.20	0.13 (p=0.19)	0.11 ± 0.17	-0.05 (p=0.63)

Table S2. Laser-evoked EEG responses in different trial categories (low-pain and high-pain trials) and subject categories (low-pain

and high-pain subjects). Data from Experiment 1.

Table S3. Two-way mixed-design ANOVA to assess the effect of trial category (low-pain vs. high-pain trials) and subject category (low-pain vs. high-pain subjects) on laser-evoked EEG responses. Data from Experiment 1.

Table S4. Three-way mixed-design ANOVA to assess the effect of trial category (low-pain vs. high-pain trials), feature category ('LEP', ' α -ERD', and ' γ -ERS'), and subject category (low-pain vs. high-pain subjects) on normalized magnitudes of laser-evoked EEG responses. Data from Experiment 1.

Three-way mixed-design ANOVA	F value	p value	Partial η^2
Trial category	41.455	< 0.001	0.068
Feature category	< 0.001	1.000	< 0.001
Subject category	0.519	0.472	0.001
Trial category \times feature category	23.932	< 0.001	0.078
Trial category \times subject category	0.042	0.838	< 0.001
Feature category \times subject category	4.882	0.008	0.017
Trial category \times feature category \times subject category	0.784	0.457	0.003
Post hoc test (LSD) for feature category \times subject category			
'LEP' magnitude	0.287	0.593	0.002
$'\alpha$ -ERD' magnitude	1.085	0.299	0.006
'γ-ERS' magnitude	7.751	0.006	0.039

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