Precise overlapping neural representations between feeling and seeing touch in people with high tactile empathy

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Abstract

Empathy allows us to understand and sometimes vicariously experience what someone else is feeling[1,2]. For some people this extends to tactile sensations, with reports of feeling touch when seeing others being touched[3,4]. Major theories claim that tactile empathy relies on overlapping neural representations between feeling and seeing touch[5–8]. Here we test this using time-resolved decoding of electroencephalography (EEG) data collected while participants felt touch to the fingers or watched videos of touch to another person's fingers. A classifier trained and tested on brain activation patterns during tactile trials could distinguish touch to the thumb versus little finger, demonstrating remarkable sensitivity to small neural differences. In people with high tactile empathy, who report feeling touch when watching videos of touch, these tactile classifiers cross-generalised to visual trials. These data show that representations of feeling and seeing touch overlap, including fine-grained information about touch location on the hand. The timing suggests that early visual predictions of touch location involve later (high-level) tactile representations. Our results demonstrate that EEG decoding can extract precise neural signatures for location of touch and suggest that shared neural representations underpin tactile empathy.

Main text

Tactile empathy may arise from overlapping neural representations between feeling and seeing touch[5–8]. Several functional magnetic resonance imaging (fMRI) studies have shown that both feeling touch and seeing another person touched evoke neural activity in similar brain areas, including somatosensory cortex[9–15] (but see[16] for conflicting findings). Two fMRI decoding studies found purely visual stimuli that implied tactile information (e.g., videos of haptic exploration of objects) could be decoded based on activity in primary somatosensory cortex[1,2]. One study using ultra-high field fMRI showed that, in some participants, simply viewing touch to fingers activated corresponding single finger representations in area 3b of the primary somatosensory cortex[17]. Combined, these findings suggest that some information when seeing touch is transferred to regions involved in processing the first-hand experience of touch, with intriguing hints that there may be individual variability. Here, we test for direct evidence that neural representations of felt and seen touch overlap, the timecourse of any convergence of information between the modalities, and whether neural overlap differs between individuals who vary in tactile empathy.

We explore the dynamic representations of felt and seen touch using multivariate pattern analysis (MVPA) of whole-brain electroencephalography (EEG) recordings. Participants were presented with tactile stimuli to the little finger or thumb, or carefully matched videos of a hand being touched in the same way. We test the timecourse and content of activation patterns evoked by directly feeling touch, and whether these tactile patterns overlap with activation evoked by visually perceived touch.

Differences in neural overlap between feeling and seeing touch may underpin individual variance in tactile empathy. For some individuals, seeing others touched results in a vicarious perception of touch, a phenomenon known as mirror-touch synaesthesia (estimated prevalence ~1.6%)[4]. We recently discovered that a substantial proportion of the general population report feeling touch

when watching videos of a hand being touched[3], but not necessarily in daily life. To test if these subjective reports are linked to neural overlap, we used our vicarious touch questionnaire[3] to divide our EEG participants into those who reported feeling touch at least once (high tactile empathy group) versus never (low tactile empathy group) when watching different videos of a hand being touched.

Following our preregistered methods (https://osf.io/9ed24/), we collected 64-channel EEG data from 40 undergraduate participants (34 datasets after exclusions; 16 high tactile empathy, 18 low tactile empathy). On tactile trials, the little finger or thumb of the participant's right hand was stimulated using two automated solenoid tactile devices. On visual trials, participants viewed videos on the screen of another person's right hand being touched on the little finger or thumb (Fig. 1a, b). The touch videos were highly controlled in terms of timing, low-level visual cues, and external touch-side (left vs. right) and differed only regarding which finger was touched, to ensure the classifier had to use touched-finger information rather than other signals. To achieve this, we used video editing software to animate one of two sticks moving identically towards the little finger or thumb of a static hand image, which was rotated slightly clockwise or anticlockwise in different videos to add low-level visual variation. Further, both the participant's own hand and the hand on the screen flipped between each run (palm up or palm down) so that touch to each individual finger occurred equally often on the left and the right. Tactile and visual trials alternated in sets of nine – felt and seen touch never occurred at the same time (Fig. 1d). To ensure that participants paid attention, they counted target trials in which the touch duration was shorter than on the other trials (Fig. 1c). These targets were discarded prior to analysis.

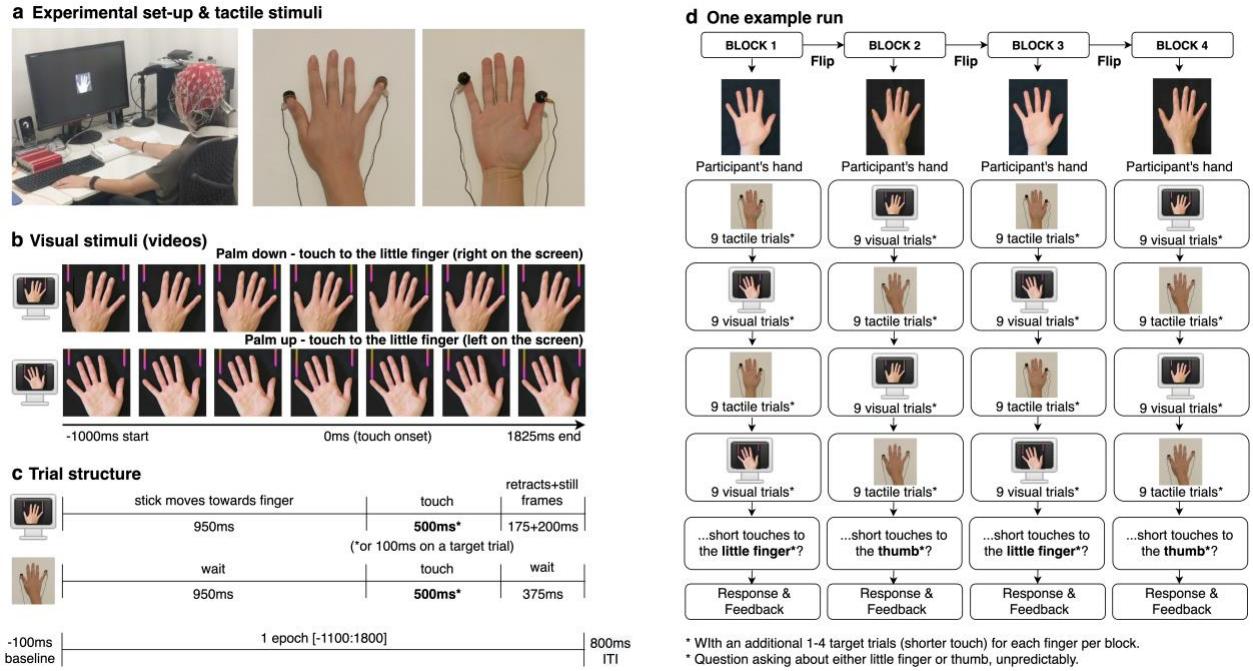
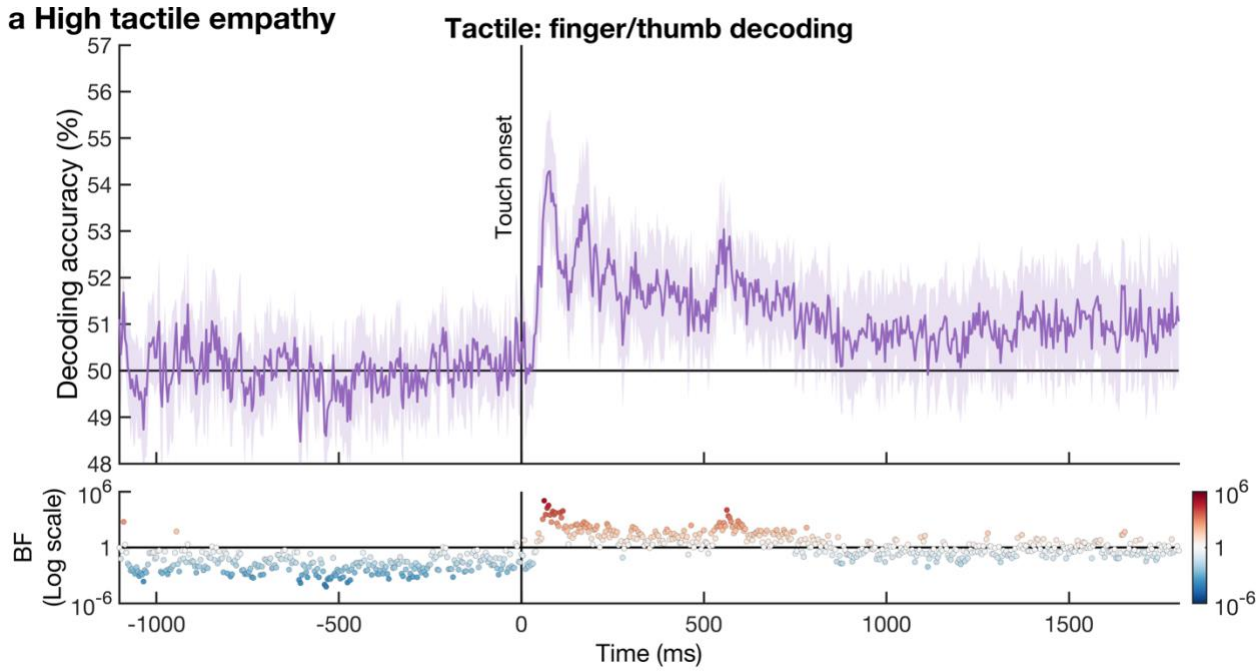
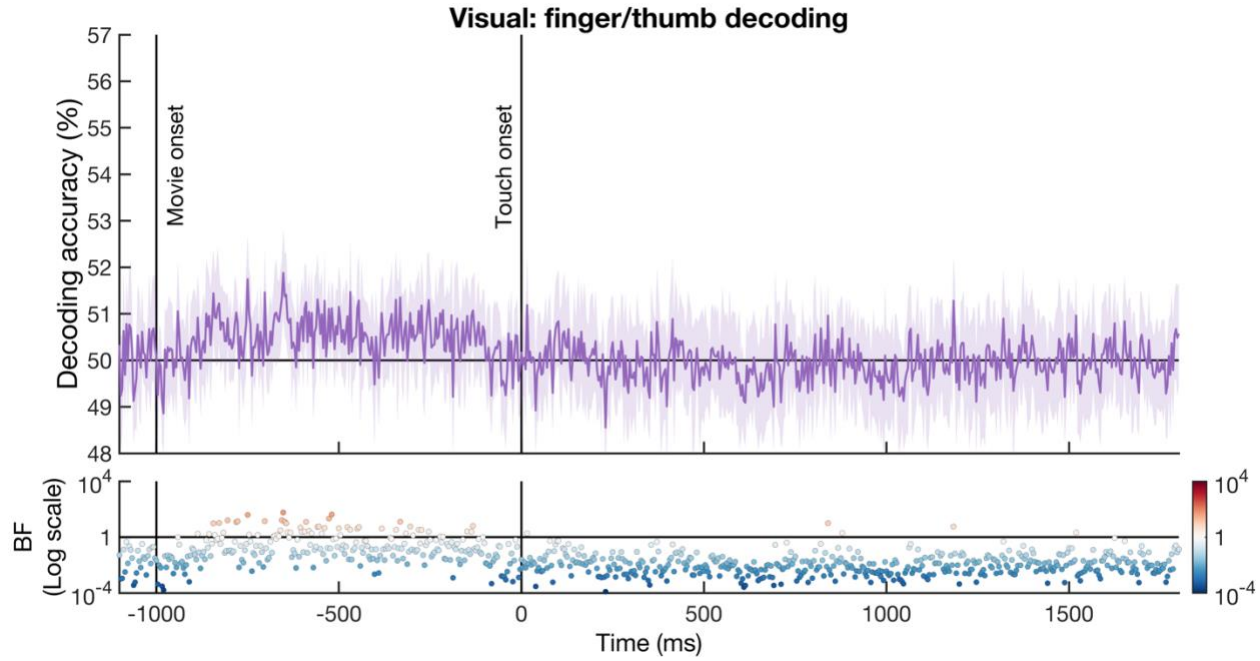


Fig 1. Experimental design, stimuli, and procedure. (a, b) Whole brain 64-channel electroencephalography data were recorded while participants' fingers were stimulated by two automated tactile devices (tactile stimuli) and while they watched videos of touch to another person's fingers (visual stimuli). **(c)** All trials lasted 1825ms with a 500ms touch period and an 800ms inter-trial-interval (ITI). Trials were epoched from -1100 to 1800ms, which includes a 100ms initial baseline. **(d)** Each run consisted

of four blocks in which participants were presented with alternating sets of nine consecutive tactile stimuli to their hand (tactile trials) and nine consecutive videos on the screen (visual trials). The orientation of the participant's own hand always aligned with the hand on the screen and both flipped between each block. Participants counted separately for the little finger and thumb how often a target (shorter touch) occurred in each block, collapsed across trial type (tactile and visual).

To assess *if* and *when* a classifier could successfully extract neural signatures regarding touch to the little finger versus thumb within each modality, we trained and tested the classifier using only the tactile *or* visual data (combining trials from both hand orientations so the classifier could only rely on information about which finger was touched). We first established decoding accuracies for each participant individually and then averaged this across participants in each group (high and low tactile empathy). We calculated Bayes factors (BF) providing evidence for the alternative hypothesis (above-chance decoding) or the null (chance decoding) at each timepoint. For tactile stimuli, the classifier was able to predict above chance (BF>10) which finger was touched from ~45ms after touch onset for both groups, and this information was maintained throughout the remainder of the trial (Fig. 2a,b top panels). For visual stimuli, the high tactile empathy group showed above-chance decoding only early in the trial, between ~170ms after video onset until ~130ms before the touch happened (Fig. 2a, bottom panel). This suggests that for these individuals, information about the perceived location of touch on another person's body is maximally present when anticipating where the touch will occur, rather than during the touch. In contrast, the low tactile empathy group showed above-chance decoding for a short period ~160ms after video onset, and again later in the trial between ~260-400ms, which is when touch (i.e., contact with the finger) occurred (Fig. 2b, bottom panel).


a High tactile empathy
Tactile: finger/thumb decoding
Decoding accuracy (%)
Touch onset
BF
(Log scale)
Time (ms)


Visual: finger/thumb decoding
Decoding accuracy (%)
Movie onset
Touch onset
BF
(Log scale)
Time (ms)

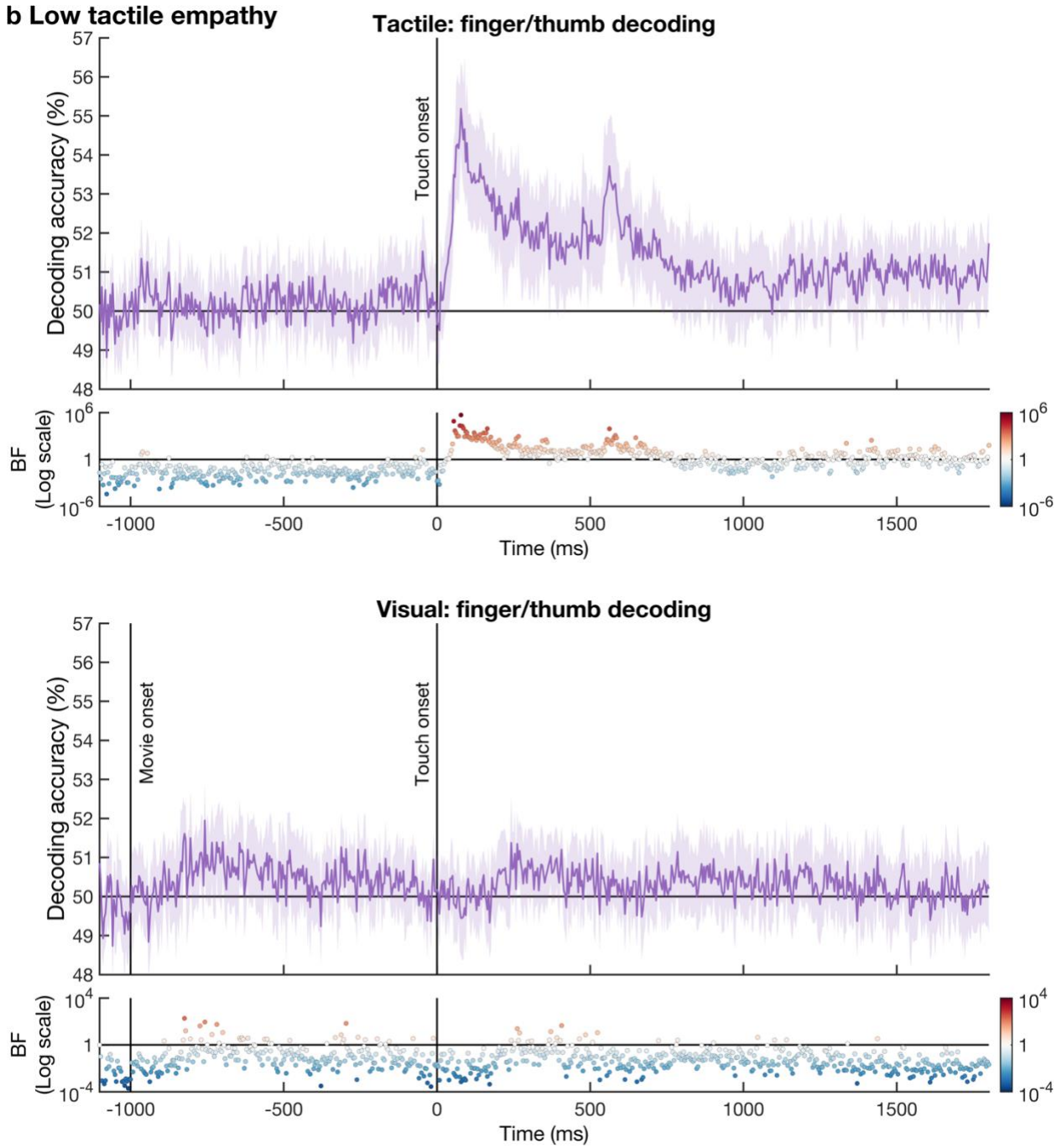


Fig 2. Touched-finger decoding within the tactile and visual modality. Mean classification accuracy over time for the **(a)** high (n = 16) and **(b)** low (n = 18) tactile empathy group. Tactile decoding plots (top) show an initial baseline period of 1100ms (100ms baseline + 1000ms wait; see Fig 1) and touch occurs between 0-500ms. The high decoding peaks occur at the onset and offset of the touch. Visual decoding plots (bottom) show an initial baseline period of 100ms followed by video onset at -1000ms and touch occurs between 0-500ms. In all plots, purple shading indicates 95% confidence intervals. Dots below plots show Bayes factors for each time point, indicating whether there is evidence for the alternative hypothesis (indicated in red: above-chance decoding) or the null (indicated in blue: chance decoding); note the different

colour bar scales for top and bottom panels. For both groups, touched-finger category can be decoded for tactile trials from ~45ms after touch onset. For the high tactile empathy group, above-chance decoding was only present early in the trial between ~170ms after the start of the video until ~130ms before the touch happened. For the low tactile empathy group, touched-finger category can be decoded for visual trials from ~160ms after the start of the video and again later in the trial between ~260-400ms, which is when touch (i.e., contact with the finger) occurs.

To test for neural overlap between feeling and seeing touch, we performed the between-modality analysis using a cross-decoding approach. We trained a classifier on activation patterns using all the tactile trials and tested it on all the visual trials[1]. Representations of the touched finger are likely to occur at different times for felt versus seen touch. To test for shared representations between the modalities, we used a time-generalisation approach, which allows us to test if the neural patterns overlap at different timepoints across the entire timeseries[18–20]. Only in the high tactile empathy group did we find strong evidence that information about the location of touch (little finger or thumb) generalised from a tactile to a visual representation (indicated in red; Fig. 3a). In this group, tactile representations from ~400ms onwards overlap with part of the visual signal, with the strongest evidence for overlap present late in the tactile trial, ~750ms after touch onset. The overlap with the visual signal is in the early part of the visual trials, from the start of the video until ~250ms before touch onset. This suggests that when participants are making predictions about where the touch will occur, based on the video, this activates later (high-level) tactile representations. The low tactile empathy group showed almost exclusively evidence for chance-decoding (indicated in white; Fig. 3b).

[1] We also did the complementary analysis, training on visual and testing on tactile trials (Extended Data Fig.1). This produced much weaker evidence for cross-decoding, presumably because of variation in the signal-to-noise ratio between the train and test sets[46].

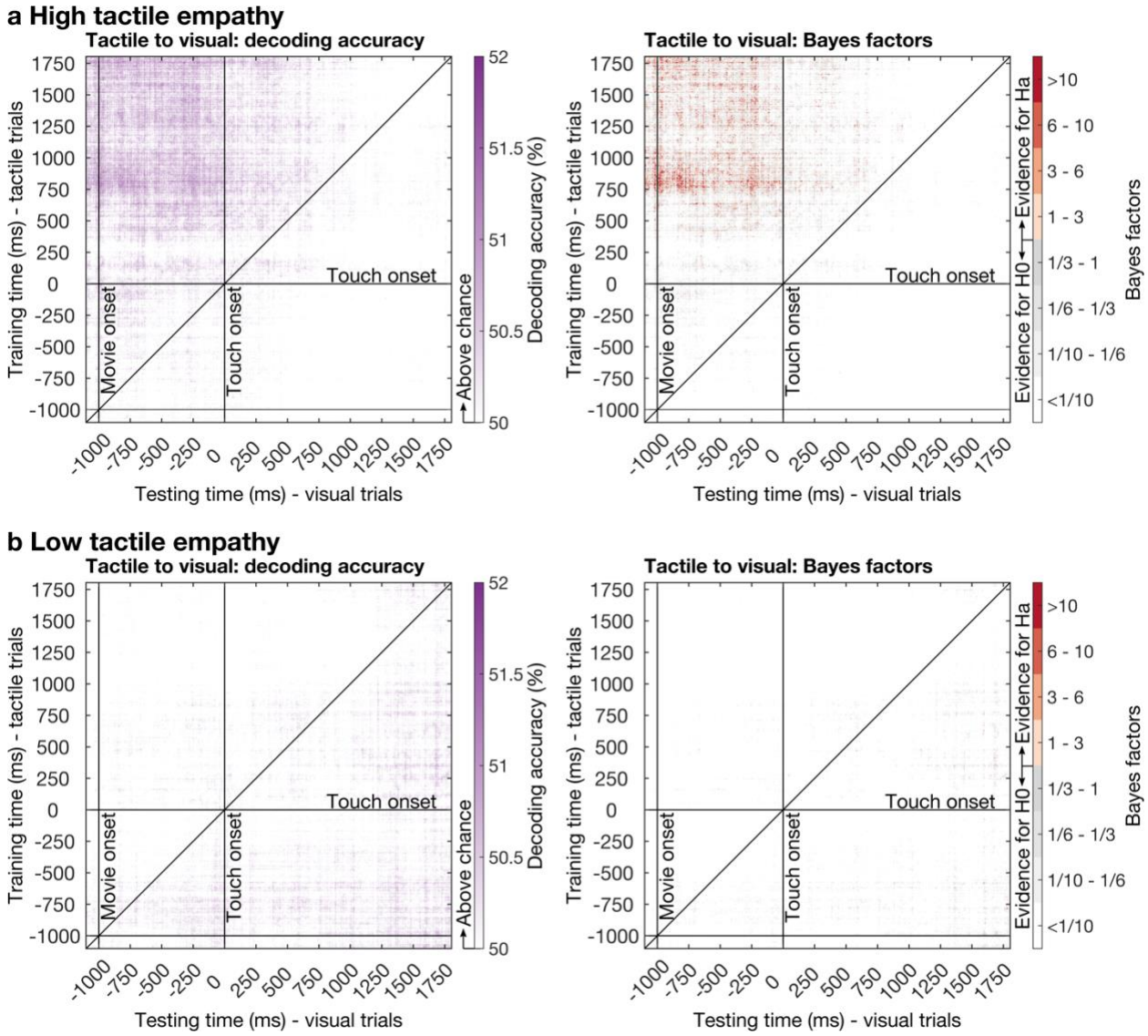


Fig 3. Strong evidence in individuals with high tactile empathy for between-modality decoding when training on tactile trials and testing on visual trials. Left plots: Mean classification accuracy for each train-test timepoint distinguishing touch to the little finger versus the thumb when training on tactile trials and testing on visual trials in the **(a)** high (n = 16) and **(b)** low (n = 18) tactile empathy group. Right plots: Corresponding Bayes factors. **(a)** Above-chance decoding (>50%; indicated in purple) when training on the late tactile signal (~400:1800ms), and testing on the early visual signal (~-1000:750ms), with the remainder of timepoint combinations showing chance-decoding (indicated in white). Corresponding Bayes factors show the strongest evidence (indicated in red) when training on ~750ms after touch onset in the tactile signal and between ~-1000 and ~-250ms in the visual signal. **(b)** Above-chance decoding (>50%; indicated in purple) is observed sparingly, with mostly at-chance decoding (indicated in white). Corresponding Bayes factors provide very little anecdotal-moderate evidence (indicated in light orange) for cross-decoding, with mostly strong evidence for chance-decoding (indicated in white).

Overall, our results demonstrate, for the first time, that we can extract dynamic neural signatures regarding the specific location of felt or seen touch on the hand. This shows the remarkable sensitivity of whole-brain EEG decoding methods, considering the close proximity of finger representations in somatosensory cortex[21]. The real benefit of using EEG, however, is the high temporal resolution, which allowed us to test for the emergence of information over time and gain insights into the content of shared representations between felt and seen touch. The within-modality decoding shows that information about which finger is touched is present very early around ~45ms for directly felt touch. In our high tactile empathy group, who reported feeling touch when watching videos of touch during our vicarious touch questionnaire, tactile classifiers cross-generalised to visual data, but at a much later stage. In this group, overlap occurred between a visual representation when the stick was still moving towards the finger, and a late tactile representation (from 400ms after touch onset). A plausible explanation is that high level tactile information, considerably more abstracted than the early initial processing of touch, is activated for these individuals during the prediction of touch location in the videos.

Previous EEG studies using univariate analyses show increased amplitude of evoked potentials in response to a tactile stimulus accompanied by a matching visual stimulus (i.e., feeling and seeing touch simultaneously) as early as 45ms (P45) and at later, more cognitive, stages (a positive peak between 200-600ms)[22–26]. These findings have led to claims that a 'mirror system' is active very early in processing[22–26]. The timecourse of our results, however, suggests that although seeing touch does activate some form of tactile representations specific enough to contain information about which finger was touched, this tactile information is from a much later time. This implies a higher level of abstraction and greater processing than early tactile signals. Our findings align with those of a univariate magnetoencephalography (MEG) study where analysis of sensors around the somatosensory cortex showed an early response to feeling touch (within 300ms) and later response when seeing the same type of touch (300-600ms)[27]. Due to the low spatial resolution of EEG, we cannot draw strong inferences about the source of activation. The observed timecourse however, does clearly suggest a distinction between the rapid somatosensory processing involved when directly feeling a tactile stimulus (~45ms[28]) and more extensive processing involved when seeing touch.

The fMRI and M/EEG studies mentioned above tested general population samples without differentiating between individuals based on reports of tactile sensations when seeing touch[10,13–15,22–26]. Two fMRI studies have compared brain activation in mirror-touch synaesthetes with non-synaesthetes, but again, no distinctions were made in the latter group[9,12]. As a result, it has remained untested whether neural differences for tactile empathy exist within the general population and if these link to the subjective experience of vicarious touch. A prominent model proposes that mirror-touch synaesthesia occurs when activation of the somatosensory cortex reaches the threshold for awareness in response to seeing someone touched, whereas in non-synaesthetes, such activation remains implicit[6,9]. Here we show that, in specific contexts, apparent non-synaesthetes report feeling touch when seeing touch, and these self-reports are linked to shared neural representations. This suggests that mirror-touch synaesthetes are not categorically different from the rest of us, but rather fall at the extreme end of a continuum of tactile empathy[29,30].

In conclusion, we demonstrate that fine-grained representations of touch location on the hand can be distinguished using whole-brain EEG decoding methods, and that people with high tactile

empathy have overlapping neural representations between feeling and seeing touch. The timecourse of this overlap implies that top-down predictions about the visually unfolding touch event evoke abstract tactile information[31]. Overall, our findings suggest that precise mapping between seeing and feeling touch is linked to tactile empathy, providing novel insight into how shared representations could underlie empathising with others.

Methods

Experimental design

Participants

We recruited naïve undergraduate students through Macquarie University subject pools. All participants reported normal or corrected to normal vision and no neurological disorders. We recruited for right-handed participants, however, one participant reported being left-handed on the post-experiment vicarious touch questionnaire. As preregistered, we tested 20 participants before we performed statistical group-level Bayesian analyses. We then used our stopping rule and continued data collection until we had sufficient evidence for either the alternative- or null hypothesis for at least 50% of the timepoints (ranging from -1100ms to 1800ms with a resolution of 4ms) for the main analyses (within- and between-modality decoding of touched finger). We interpreted a Bayes factor of 6 (or 1/6 in case of evidence for the null) as sufficient evidence[32,33]. We tested 40 participants in total and six participants were excluded due to their performance on the experimental task being below the pre-specified threshold of 60% correct. Our final sample after exclusions consisted of 34 participants (27 female, mean age = 22 years (SD = 5); age range: 18-40 years). Of these, 16 were classified as high tactile empathy and 18 as low tactile empathy based on their responses to the post-experiment vicarious touch video questionnaire (see below). Participants provided written consent and either received $20 per hour or course credit in return for participation. The study was approved by the Macquarie University Ethics Committee.

Stimuli

The visual stimuli consisted of 1825ms videos showing a single touch to either the little finger or thumb of a female right hand placed on a dark grey background. The start of each video shows an image of the same hand and two pointy metal sticks placed above the top of the little finger and thumb. As soon as the video starts, one of the sticks moves towards the finger (0-950ms), touches it for 500ms (950-1450ms) before retracting (1450-1650ms) and finally remaining still (1650-1825ms; the other stick remains still throughout). We controlled the exact movement and timing of the stick by overlaying images of the stick with an image of the hand and animating it using Adobe After Effects[34]. We also added shading to make the touch look realistic. We coloured the sticks with a red/pink/orange gradient to increase the saliency of the stick motion. To ensure that the classifier could not rely on irrelevant spatial information, such as whether the stick is moving on the left or the right of the screen, the videos show the hand palm up or palm down so that in some cases a finger (little finger or thumb) was located on the left and other times on the right (Fig. 1b). We also rotated the hand slightly clockwise and anticlockwise in different videos so that the top of the little finger and thumb were either horizontally aligned or one was placed higher than the other. This resulted in 12 different videos which were shown an equal number of times throughout the experiment (videos available at: https://osf.io/9ed24/). On target trials we showed

the same videos as described above but removed several of the frames in the middle to create a shorter touch (100ms instead of 500ms). To keep the length of the normal and target videos identical, we added frames at the end of the target videos. All videos were presented in the middle of the screen at a size of 320x320 pixels, on an AOC 27" 144Hz Monitor. Videos were presented at a sampling rate of 40 frames per second on a monitor with a refresh rate of 120Hz, resulting for each video in 73 frames being presented in 1825ms.

The tactile stimuli consisted of a tap to the little finger or thumb of the participant's right hand, which lasted for 500ms (normal trials) or 100ms (target trials) (i.e., the same length as the touch in the videos). As with the visual trials, we added 400ms to the end of each target trial to maintain the same trial duration. The tap was produced by two electromagnetic solenoid-type vibrotactile stimulators (diameter: 18mm, height: 12mm) with a small round probe (diameter: ~3mm, maximum extension: ~2mm) attached with tape to the top of the fingers (Dancer Design, St. Helens, UK; dancerdesign.co.uk) (Fig. 1a).

Procedure

Participants were seated in a dimly lit room with the EEG cap fitted so that the electrode Cz was located over the vertex. The participant's hand was placed in front of the participant on the table and aligned with the middle of the computer screen. Two small tactile devices were attached to the tip of the little finger and thumb (of the right hand). To mask potential noise from the tactile devices, we played white noise through speakers located on both sides of the computer screen and participants wore earplugs. After set-up was completed, participants received both verbal and written instructions and performed a test run. Once the experimenter confirmed that the task was clearly understood, the participant started the experiment by pressing the space bar.

We presented participants with alternating sets of nine consecutive touches to their own hand (touch trials) and nine consecutive touch-videos on the screen (visual trials). Whether the run started with tactile or visual trials was counterbalanced between participants and runs. Tactile and visual stimuli were never presented at the same time. The hand orientation (palm up or palm down) in the videos changed after each block of 36 trials, and participants were instructed via a text prompt and image on the screen to flip their own hand in the same way. This ensured that the touch side for each finger always aligned between the modalities. We counterbalanced the modality, hand orientation (and thus external touch side), and touched finger within each experimental run for each participant. We also controlled the number of consecutive touches to the same finger.

The task was for the participant to count how often a target (shorter touch) occurred in each block for the little finger and thumb separately. Targets felt to the hand and seen on the screen had to be combined. There were always 1-4 targets per finger per block. The task ensured that participants were paying attention to which finger was touched. After each block, a question was presented on the screen asking how many short touches the participant counted to *either* the little finger or thumb (which was probed was pseudorandom and counterbalanced). Participants answered with a number ranging from 0-9 using the numeric keypad on the keyboard and were instructed to start counting again from zero each time a new block started. Feedback about whether the response was correct or incorrect, and the right answer, was provided on the screen after each response.

There were 12 runs in total, divided into four blocks of 36 trials (with alternating sets of nine tactile and nine visual trials) resulting in a total of 1728 trials (864 tactile and 864 visual). There were an additional 240 target trials (20 per run), which were excluded from analysis. Between trials there was an inter-trial-interval (ITI) of 800ms. Each run lasted approximately 7-8 minutes with short breaks between blocks and runs. Participants controlled the length of each break and continued by pressing the space bar.

To reduce eye-movements, participants were instructed to fixate on a white fixation cross that was shown in the middle of the screen (on top of the hand during videos) throughout the entire experiment (including during tactile trials). However, it is important to note that eye movements are not a confounding factor interpretable by the classifier as signal, because in our experimental design the external touch side is orthogonal to the touched finger. Stimuli were presented using MATLAB (2019a, MathWorks) with Psychtoolbox[35–37]. We used parallel port triggers to mark relevant timepoints in each trial.

After the main experiment, each participant filled out a short questionnaire consisting of three parts to assess for vicarious touch experiences. First, we showed 10 videos of a 'neutral' (i.e., neither pleasant nor unpleasant) touch to a Caucasian female hand on a black background presented in the first-person perspective. After each video we asked participants to indicate if they felt a tactile sensation on their own body, and if so, where the touch was felt (this is a short version of our longer vicarious touch questionnaire[3]). Second, we asked participants if they felt a touch on their own fingers when presented with the visual stimuli during the experiment. Third, we used a short five question Empathy Quotient scale[38] to assess emotional reactivity, a dimension of empathy that relates to predicting other people's thoughts and feelings. The entire session took approximately three hours.

EEG data acquisition

Continuous EEG activity was recorded at a sampling rate of 2048Hz using a 64-channel Active-Two BioSemi active electrode system (BioSemi, Amsterdam, The Netherlands). This system uses a preamplifier stage on the electrode which corrects for high impedances[39]. The offset voltage was kept below 20 mV (BioSemi recommends below 50 mV). EEG electrode placement was in line with the international 10/20 standard. The EEG system was connected via a fibre optic cable to a Dell Precision T3620 computer which runs Windows 10. Data acquisition was monitored through the BioSemi acquisition software on an iMac with macOS version 10.14.1.

Analysis

Vicarious touch questionnaire

Based on previous research findings[9,12], we anticipated that individuals who report vicarious touch sensations would have stronger neural overlap between feeling touch themselves and seeing someone else being touched, compared to those who never experience this. We therefore divided our sample (n = 34) into individuals with high and low tactile empathy based on whether they answered feeling touch on their own hand (left or right) for *at least one* of the 10 videos. First, we asked: "While watching the video, did you experience a tactile sensation on YOUR body?". If someone answered 'yes' to the first question, we also asked 'Where on YOUR body did you feel the tactile sensation?' Of the 17 participants that answered 'yes' to the first question, 16 indicated

the sensation was localised either to the left hand (n = 8), the right hand (n = 4) or to alternating/both hands (n = 4). One participant indicated that the mirrored sensation was 'a general feeling' and thus we placed this participant in the low tactile empathy group (n = 18). Three participants belonging to the high tactile empathy group also answered 'yes' to the question: "During the experiment you just participated in, did you feel a touch on your own body when you saw the metal stick in the video touch the hand on the screen?" One participant wrote the following description: "I felt the touch on my right hand, sometimes on my thumb and sometimes on my pinky depending on where the metal stick touched the hand on the screen." None of the participants in the low tactile empathy group answered 'yes' to this question. We used a Bayesian Mann-Whitney U test to assess whether the high tactile empathy group also scored higher on the emotional reactivity empathy scale. This provided evidence (BF 1/7) for the null hypothesis, suggesting that this group was higher specifically in tactile empathy and not emotional reactivity.

EEG data analysis

We first downsampled the data to 256Hz using the EEGLAB toolbox[40] and re-referenced to the common average. Following a recent pre-processing method we applied trial-masked robust detrending[41] using the Amsterdam Decoding and Modeling toolbox[42]. Like regular robust detrending[43], this method removes slow drifts in the data by first identifying glitches, which are subsequently masked out before fitting an nth order polynomial and subtracting the fit. In addition, trial-masked robust detrending also masks out cognitive events of interest, and thus the polynomial does not fit to an actual ERP, which may otherwise result in temporal displacements or the subtraction of a real effect (for a more detailed description and the benefits over high- and low-pass filtering see ref [41]). We epoched and masked the data from -1100 to 1802ms (relative to the onset of touch), added a pad length of 50s, and fitted a 30th order polynomial. We specified to mask current events and bad data, and to remove bad channels before fitting the polynomial. For two participants, we were unable to detrend with bad data masked. On visual inspection these datasets were normal, so we included them without the masking. We kept epochs the same length between the tactile and visual trials for easier interpretation of the data. However, whereas touch in the visual trials only starts at 0ms, the onset of the visual trials (i.e., the start of the video) is before 0ms (at -1000ms) and participants were able to anticipate early in the trial which finger would be touched (Fig. 1c). We applied baseline correction from -1100 to -1000 (i.e., 100ms) for both the tactile and visual trials. We did not perform any other pre-processing steps such as channel selection or artefact correction[44].

Time-resolved multivariate pattern analysis

We applied time-resolved multivariate pattern analysis to our EEG data using MATLAB and the CoSMoMVPA toolbox[45]. For each participant, we extracted the pattern of activation across all 64 EEG channels at each timepoint and used this to train and test a linear discriminant analysis (LDA) classifier. Our classification performance metric was the average decoding accuracy across participants, for each timepoint (or timepoint combination), with 50% chance level. We performed both within- and between-modality decoding.

Within-modality decoding

First, we tested whether the pattern of activation contained information regarding which finger was touched within each modality separately (combining trials from both hand orientations) at each timepoint. We used a leave-4-out cross-validation where we iteratively trained a classifier on

all but four trials (one of each stimulus option, randomly selected: palm up, vs. palm down; touch to little finger vs. thumb) and tested it on the four left out trials. We only trained and tested the classifier on the same timepoints (e.g., train on 100ms and test on 100ms), as we expected that above-chance decoding would be strongest along the diagonal (as we are training and testing on the same signal). Results were averaged across participants. Statistics were performed on the group level.

Between-modality decoding

To test for neural overlap between feeling and seeing touch, we trained a classifier on all tactile trials and tested it on all visual trials (864 trials per modality). As information distinguishing which finger was touched might be present at different timepoints for tactile and visually perceived touch, we used temporal generalisation methods where a classifier is trained and tested on all timepoint combinations[18–20]. This method gives a time-time decoding matrix where each cell represents the average classification accuracy at that particular train-test timepoint (Fig. 3). Again, we averaged across participants and performed the group level analyses on the high and low tactile empathy group separately. If representations are present at the same time, above-chance decoding will appear along the diagonal, and if they occur at different train-test timepoints, above-chance decoding will be off the diagonal. We also trained the classifier on visual trials and tested it on tactile trials which produced similar but weaker results (Extended Data Fig.1). This asymmetry in the direction of generalisation is likely due to variation in signal-to-noise between datasets[46], and may reflect the greater temporal uncertainty in the videos which increases the trial-by-trial and between-participant variability in the visual domain.

Statistical inference

We ran Bayesian t-tests at each timepoint (using the Bayes Factor R package[47]) to establish the amount of evidence for either the alternative hypothesis (above-chance decoding; indicated by a Bayes factor > 1) or the null hypothesis (chance decoding; indicated by a Bayes factor < 1)[48]. We used a point-nil for the null-hypothesis and specified a half-Cauchy prior for the alternative hypothesis with medium width (r = 0.707) that covered an interval with effect sizes ranging from 0.5 to infinity. We chose this prior range because previous studies that looked at visual decoding found effect sizes as large as 0.5 during a baseline period when there cannot be any meaningful information in the signal[49]. We also performed a robustness check with a wide (r = 1) and ultrawide (r = 1.414) prior which did not have a pronounced effect on the results. We interpret a Bayes factor of 6 (or 1/6 in case of evidence for the null) as substantial evidence[48]. We use a conservative criterion for accepting above-chance decoding: a single timepoint above-chance decoding may reflect noise, so we only consider evidence that classification accuracy is above chance for two consecutive timepoints based on a Bayes factor > 6 to infer that the data at that time contain information about the location of touch.

Preregistration

We preregistered this study, including a detailed analysis plan, on the Open Science Framework (OSF) before data collection. We deviated from our preregistration in three ways. First, we used trial masked robust detrending instead of applying a high- and low-pass filter as this has recently (after preregistration) been shown to introduce fewer artifacts, especially for time generalisation[41]. Second, for the within-modality decoding, we modified the folds as the EEG task lasted for approximately two hours and participants reported that it was demanding, making it likely that

physiological artifacts (e.g., blinking, moving, sweating) and cognitive artifacts (e.g., tiredness, lack of concentration) would increase throughout the task. Initially we planned to use a twelvefold cross-validation where we train the classifier iteratively on 11 runs and test it on the left out run, but this could be influenced by any drift or change across the experiment. Instead, we used a leave-4-out approach, where we iteratively trained on all but four trials (one of each stimulus option: palm up, vs. palm down; touch to little finger vs. thumb) and tested it on the four left out trials. This way, we train the classifier on trials from the beginning, middle and end of the experimental task. Finally, we also applied a baseline correction for the within-modality analysis. Using baseline correction before decoding has been shown to increase the likelihood of picking up on an effect without introducing artefacts (at least when trial-masked robust detrending is used rather than high-pass filtering)[41], potentially by reducing temporal drifts due to internal and external sources[50].

Data and code availability
Raw data and analysis scripts are available on OSF: https://osf.io/9ed24/.

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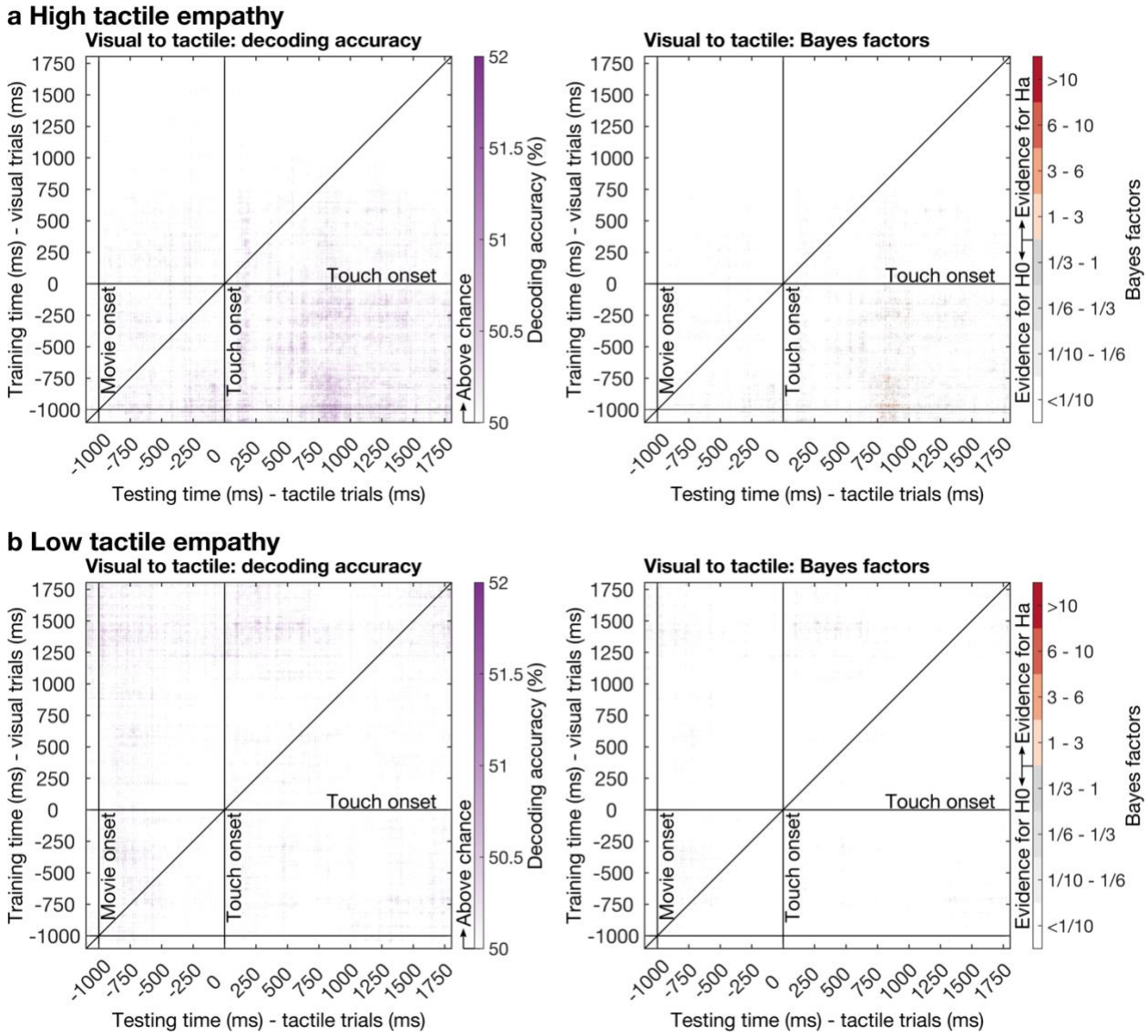

Extended Data Fig 1. Between-modality decoding in the high and low tactile empathy groups when training on visual trials and testing on tactile trials. Left plots: Mean classification accuracy for each train-test timepoint distinguishing touch to the little finger versus the thumb when training on visual trials and testing on tactile trials in the **(a)** high (n = 16) and **(b)** low (n = 18) tactile empathy group. Right plots: Corresponding Bayes factors. **(a)** Some above-chance decoding (>50%; indicated in purple) at a very similar timecourse when training on tactile trials and testing on visual trials (see Fig 3 main text). Right plot: Corresponding Bayes factors provide little evidence for cross-decoding (indicated in light orange). This could be due to variation in the signal-to-noise ratio between the train and test set. (**b**) Very little above-chance decoding (>50%; indicated in purple) is observed. Right plot: Corresponding Bayes factors provide predominantly strong evidence for chance-decoding (indicated in white).