Shared representations between seeing and feeling touch in people with high tactile empathy

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Abstract

Simulation theories propose that tactile empathy arises when seeing someone else being touched triggers corresponding representations of being touched. Prior electroencephalography (EEG) findings show that feeling touch while simultaneously seeing touch (versus seeing a no-touch stimulus) modulates early somatosensory responses. Functional Magnetic Resonance Imaging (fMRI) studies have shown that seeing touch increases somatosensory cortical activation. These findings have been taken to suggest that when we see someone being touched, we simulate that touch in our sensory systems. The overlap between somatosensory activation when seeing and feeling touch differs between individuals, potentially underpinning variation in tactile empathy. Increases in amplitude (EEG) or cerebral blood flow response (fMRI), however, are limited in that they cannot test for the information contained in the neural signal: seeing touch may not activate the same information as feeling touch. Here, we use time-resolved multivariate pattern analysis on whole-brain EEG data from people with high and low tactile empathy to test whether seen touch evokes similar representations to the first-hand experience of touch. Participants felt touch to the fingers (*tactile* trials) or watched carefully matched videos of touch to another person's fingers (*visual* trials). In both groups, EEG was sufficiently sensitive to allow decoding of touch location (little finger vs. thumb) on tactile trials. Only in individuals who reported feeling touch when watching videos of touch (high tactile empathy) could a classifier trained on *tactile* trials distinguish touch location on *visual* trials. This demonstrates that, for these people, there is similarity between the neural pattern when seeing touch and feeling that same touch. The timecourse of this overlap shows that seeing touch evokes similar representations to *later stages* of tactile processing. Therefore, while simulation may underlie tactile empathy, our findings suggest this involves abstract high-level processes rather than early low-level processes.

Introduction

Simulation theories propose that we empathise with others by mapping the observed state onto a similar representation within our own system (Bird and Viding, 2014; Gallese et al., 2004; Gazzola et al., 2006; Keysers and Gazzola, 2009; Lamm et al., 2016). This applies not only to actions and emotions but also to sensations (Keysers and Gazzola, 2009). Empathy for tactile sensations (i.e., 'tactile empathy') would then rely on evoking similar neural representations when we see someone touched as when we feel touch directly (Bufalari and Ionta, 2013; Keysers and Gazzola, 2009).

Electroencephalography (EEG) studies show that seeing touch can modulate both early (45ms) and late (200-600ms) somatosensory activity (Adler et al., 2016; Adler and Gillmeister, 2019; Bufalari et al., 2007; Deschrijver et al., 2016; Martínez-Jauand et al., 2012). For instance, Adler and colleagues (2016, 2019) simultaneously presented visual stimuli showing touch to a hand with tactile stimulation of the participant's hand. Seeing the touch, compared to seeing a no-touch stimulus, modulated activity measured from electrodes centred on the somatosensory cortex at very early timepoints (~45ms; P45). As the P45 is likely to reflect activity in the primary somatosensory cortex (Allison et al., 1992; Schubert et al., 2008), they inferred that this modulation reflected shared touch representations at *early sensory-perceptual* processing stages (Adler et al., 2016; Adler and Gillmeister, 2019; Bufalari et al., 2007), consistent with simulation theories for tactile empathy.

Studies using functional Magnetic Resonance Imaging (fMRI) report that seeing another person being touched evokes activity in brain regions typically responsive to the first-hand experience of touch (for reviews see Bufalari and Ionta, 2013; Gillmeister et al., 2017; Keysers et al., 2010). For example, Keysers et al. (2004) were the first to demonstrate that seeing brush strokes to another person's legs caused similar activation in the secondary somatosensory cortex as having one's own legs stroked. Subsequent studies have further shown that seeing touch activated both the primary (Blakemore et al., 2005; Kuehn et al., 2013; Schaefer et al., 2009) and secondary somatosensory cortex (Ebisch et al., 2008; Keysers et al., 2004). Based on these findings, Keysers and colleagues (2009, 2010, 2022) propose that somatosensory activation in response to observing touch could underlie our ability to understand others' tactile experiences.

There are also intriguing hints that there is individual variability in the degree to which the somatosensory cortex is activated by seen touch. A recent ultra-high field fMRI study showed that simply viewing touch to another person's fingers can activate fine-grained single finger maps in area 3b of the primary somatosensory cortex similar to directly feeling touch (Kuehn et al., 2018). However, not all participants showed this visually evoked somatosensory effect, and for those who did, some showed almost perfect overlap between tactile- and visually-driven activation whereas others had non-overlapping tactile/visual activations. If neural overlap between seen and felt touch indeed underlies tactile empathy, this could explain individual variability in how often and intensely people empathise with another's sensations (for a review see Gillmeister et al., 2017). For instance, mirror-touch synaesthetes, who feel touch on their own body when they see someone being touched (possibly

indicating ‘extreme’ tactile empathy), show stronger somatosensory activation when viewing touch to others compared to controls (Blakemore et al., 2005; Holle et al., 2013). This provides preliminary evidence that the strength of shared touch representations could link to subjective differences in how we perceive touch to others.

The strong prediction of simulation theories of tactile empathy is that the *information* in the neural signal about a seen touch is the same (or similar) to that of directly experiencing the touch. However, the ‘shared activation’ shown in the above univariate studies does not actually test this prediction (Lamm et al., 2016; Lamm and Majdandžić, 2015). Multivariate pattern analyses (MVPA or ‘decoding’ methods) can test for the similarity between neural representations when one is touched versus observing touch to another. By using EEG, we can test whether such similarity exists, and if so, when the overlap occurs. For our main analysis, we train a machine learning classifier at each timepoint to distinguish neural activation patterns when participants are touched on the little finger versus thumb (*tactile* trials) and test it on data when they *see* touch to the little finger versus thumb (*visual* trials; *between-modality* decoding). Our visual and tactile stimuli are carefully matched and controlled so that the classifier can only rely on information regarding the location of touch. If the classifier performs above chance, we can conclude that, at those timepoints, there are *shared representations between seeing and feeling touch* that include the precise location of touch. We also test the tactile classifier on independent (left-out) tactile trials (*within-modality* decoding) to identify *when* the location of a felt touch is reflected in the neural pattern for comparison with the timecourse of any *between-modality* decoding.

We assess these representations separately in individuals with high and low tactile empathy to explore the degree to which shared representations might underlie tactile empathy. In our study, we define these groups based on whether people report tactile experiences while watching videos of different types of touch (Smit et al., in prep). MVPA allows us to analyse each participant separately by training and testing the classifier on neural activation patterns specific to that individual. This makes our approach particularly useful when considering potential individual variation in shared touch representation.

The use of time-resolved EEG decoding allows us to test *when* any overlap between seeing and feeling touch occurs, which can tell us more about the underlying mechanisms. Simulation theories typically

propose that seeing touch should evoke *sensory* representations of being touched. This would show up as early tactile information being represented in the visual signal. This could occur due to 'direct matching' of the seen touch with corresponding representations of the felt touch (e.g., Iacoboni et al., 1999; Rizzolatti et al., 2001; Rizzolatti and Sinigaglia, 2016). Alternatively, it could be due to predictive processes: seeing a touch results in prediction that one will feel touch; the resulting prediction error (when no touch occurs) is 'explained away' by activating somatosensory cortex (Bach and Schenke, 2017; Ishida et al., 2015). Either way, the timecourse of overlap between seen and felt touch will be informative about the level at which any simulation occurs.

The goal of the present study is to provide a more detailed understanding of the processing underlying shared touch representation and how it links to variation in tactile empathy. We use time-resolved MVPA of whole-brain EEG data recorded while participants directly felt touch to different fingers or saw another person similarly touched (for the preregistration see: https://osf.io/9ed24/). We examine, in high and low tactile empathy participants, *if* representations between seeing and feeling touch are shared, and if so, *when* these are present. This tests whether shared touch representations are indeed of an early (sensory) processing stage in line with simulation theories.

Materials and Methods

Participants

We recruited right-handed naïve undergraduate students through Macquarie University subject pools. All participants reported normal or corrected to normal vision and no neurological disorders. 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; see below). We interpreted a Bayes Factor (BF) of 6 (or 1/6 in case of evidence for the null) as sufficient evidence (Dienes, 2011; Wetzels et al., 2011). We tested 40 participants in total; 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

We recorded EEG data while participants felt touch or saw touch to another person. On *tactile* trials, the little finger or thumb of the participant's right hand was stimulated, and 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). To control for external touch-side (left vs. right), 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 of the screen.

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 showed 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 started, one of the sticks moved towards the finger (0-950ms), touched it for 500ms (950-1450ms) before retracting (1450-1650ms) and finally remaining still (1650-1825ms; the other stick remained 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 (Christiansen, 2013). 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 half of the time a finger (little finger or thumb) was located on the left and other half 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. Each video consisted of 73 frames which were 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). 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).

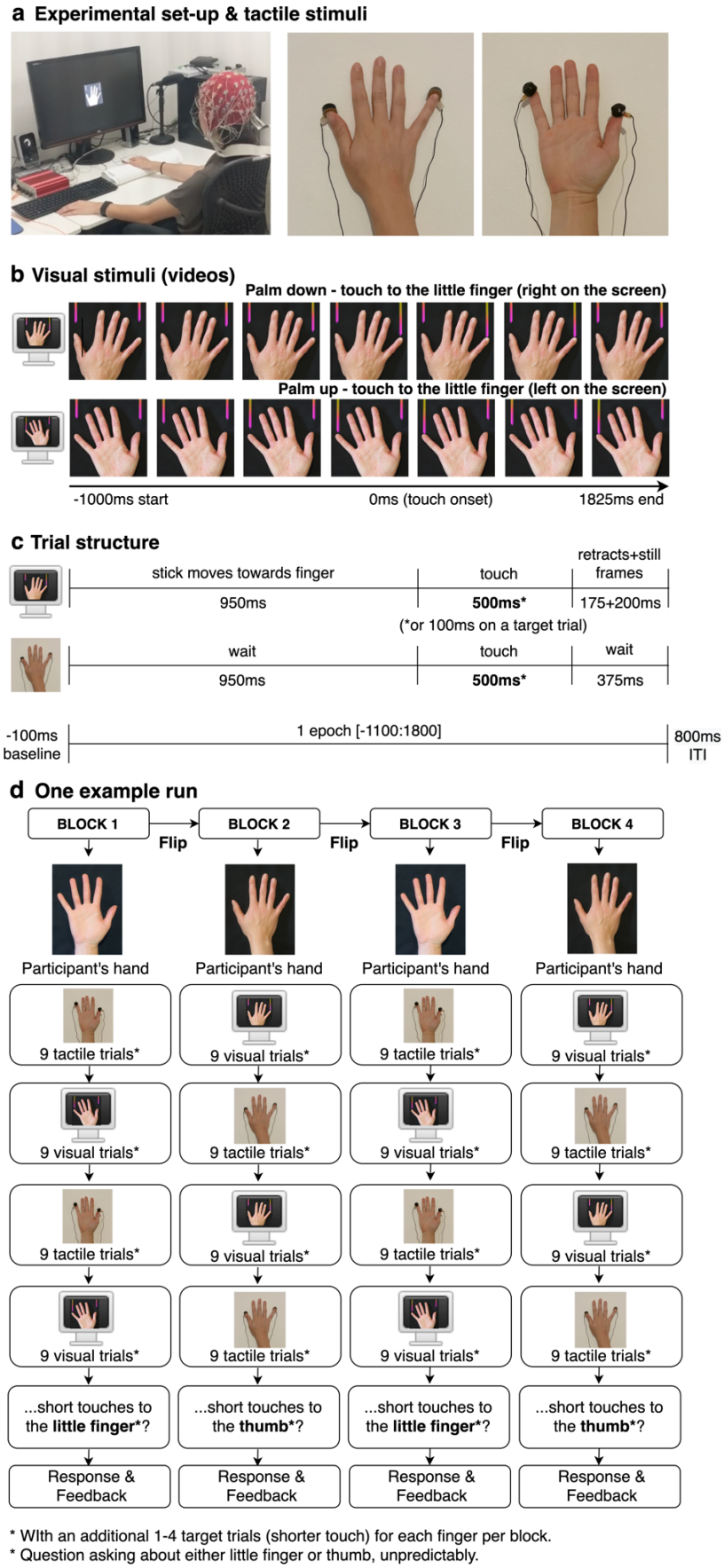


Figure 1. Experimental design, stimuli, and procedure. (**a, b**) Whole brain 64-channel EEG data were recorded while participants' fingers were stimulated by two automated tactile devices (*tactile* stimuli) and while they watched videos of touch to another person's fingers (*visual* stimuli). (**c**) Trial timing. Total trial length matched between tactile and visual trials (1825ms) with 950ms before the touch occurred and 375ms post-touch. (**d**) Each run comprised four blocks of alternating sets of nine tactile trials and nine visual trials. The orientation of the participant's hand always aligned with the hand on the screen and both flipped between each block. Participants counted how often a target (shorter touch) occurred in each block separately for the little finger and thumb, collapsed across trial type (tactile and visual).

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 on the table in front 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 auditory 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 (Fig. 1d). 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 counterbalance across each run how often one trial followed on from another in order to avoid baseline issues in the decoding analysis. For example, after the little finger is touched, the next trial can be either another touch to the little finger or to the thumb (the options are little finger -> little finger, little finger -> thumb, thumb -> thumb, thumb -> little finger). We limited how often one finger could be touched in a row to a maximum of four times.

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; these trials were eliminated prior to analysis. Targets on visual and tactile trials had to be combined. The task ensured that participants were paying attention to which finger was touched but the design ensured that any task-related rehearsal or labelling strategy could not distinguish the conditions we were asking the classifier to decode. Specifically, while participants might be rehearsing (for example) "2 little finger, 1 thumb" across trials, there was no motivation to label "touch to thumb" or "touch to little finger" on each trial. There were always 1-4 targets per finger per block. 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; see Fig 1d). 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 (Brainard and Vision, 1997; Kleiner et al., 2007; Pelli, 1997). 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 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 (Smit et al., in prep). 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 (Muncer and Ling, 2006) 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 (Metting van Rijn et al., 1990). 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.

Analyses

Vicarious touch questionnaire

Based on previous research findings (Blakemore et al., 2005; Holle et al., 2013), 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 (as pre-registered) 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 the participant answered 'yes' to the first question, we then asked 'Where on YOUR body did you feel the tactile sensation?' Of the 17 participants who 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 we therefore 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 for the null hypothesis (BF = 0.126; no greater emotional reactivity).

EEG analysis

We first downsampled the data to 256Hz using the EEGLAB toolbox (Delorme and Makeig, 2004) and re-referenced to the common average. Following a recent pre-processing method, we applied trial-masked robust detrending (van Driel et al., 2021) using the Amsterdam Decoding and Modeling toolbox (Fahrenfort et al., 2018). Like regular robust detrending (de Cheveigné and Arzounian, 2018), 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 event related potential (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 (van Driel et al., 2021). 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 (Grootswagers et al., 2017).

Time-resolved multivariate pattern analysis

We applied time-resolved multivariate pattern analysis to our EEG data using MATLAB and the CoSMoMVPA toolbox (Oosterhof et al., 2016). 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.

Decoding analyses

For the high and low tactile empathy groups separately, we tested whether neural overlap is sufficiently fine-grained such that a classifier trained on activation patterns associated with touch to the little finger versus thumb in one modality could successfully distinguish brain activation in the other modality (*between-modality* decoding). We anticipated that *between-modality* decoding might only be present for the high-tactile empathy group. However, we postulated that for both groups, a classifier should be able to extract neural signatures regarding which finger is touched *within each modality.* To verify successful within-modality decoding, we also trained and tested the classifier only on tactile *or* visual trials. We established decoding accuracies for each participant individually and then averaged across participants in high and low tactile empathy groups separately.

Between-modality decoding

To test for neural overlap between seeing and feeling 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 (Carlson et al., 2011; King and Dehaene, 2014; Meyers et al., 2008). This method gives a time-time decoding matrix where each cell represents the average classification accuracy at that particular train-test timepoint (Fig. 2). We 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.

Within-modality decoding

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.

Statistical inference

For our between- and within-modality decoding with each group, we ran Bayesian t-tests at each timepoint 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: Jeffreys, 1998). For our between-group comparison, we ran a Bayesian t-test at each timepoint comparing the high and low tactile empathy groups. For all Bayesian analyses we used the Bayes Factor R package (Morey et al., 2015). We used a half-Cauchy prior with medium width (r = 0.707) and adjusted the prior range of the alternative hypothesis from 0.5 to infinity to allow for small effects under the alternative hypothesis (Rouder et al., 2009). We chose this prior range because previous studies using visual decoding found effect sizes as large as 0.5 during a *baseline* period when there cannot be any meaningful information in the signal (Teichmann et al., 2021). 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 (Jeffreys, 1998). 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 four 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 (van Driel et al., 2021). 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: van Driel et al., 2021), potentially by reducing temporal drifts due to internal and external sources (Tanner et al., 2016). Finally, we had pre-registered to analyse high and low tactile empathy groups separately but not specifically the between-group statistical comparison, which we conducted to assess whether the high empathy group were statistically different from the low empathy group (as opposed to just being able to state that they show an effect, whereas the low group showed evidence for no effect).

Data availability

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

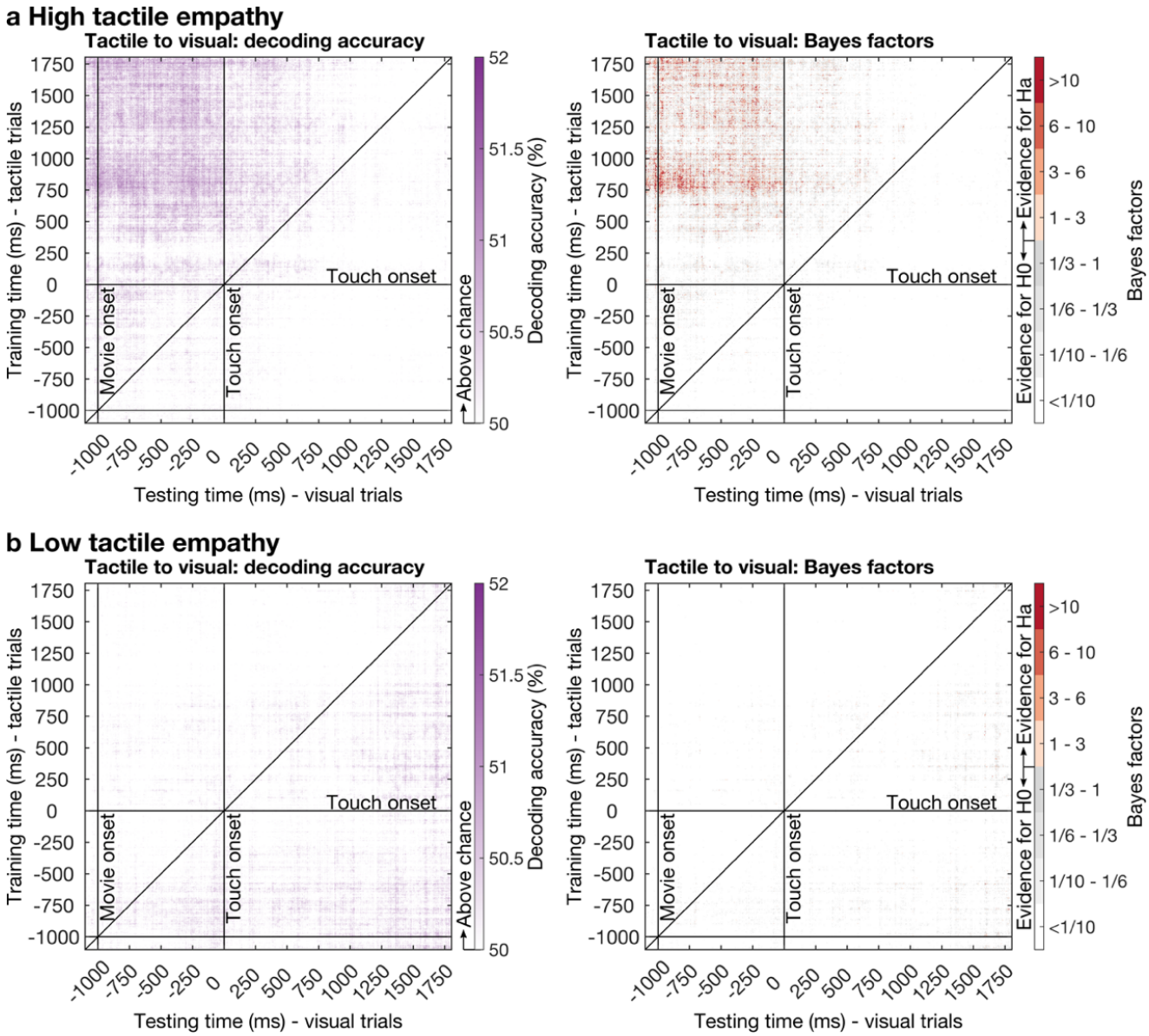
Results

Our final sample after exclusions consisted of 34 participants and 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 (Smit et al., in prep).

Between-modality decoding

In the high tactile empathy group, we found strong evidence that information about the location of touch (little finger or thumb) generalised from a *tactile* to a *visual* representation (Fig. 2a right panel; red). In this group, tactile representations from ~400ms onwards overlap with part of the visual signal, with strongest evidence for overlap being the late tactile representation (~750ms after touch onset) appearing in the early part of the visual signal (video start until ~250ms before touch onset). This suggests high-level tactile information, considerably more abstracted than initial processing of touch, is activated for these individuals during the prediction of touch location in the videos. The low tactile empathy group showed almost exclusively evidence for chance-decoding (Fig. 2b right panel; white). We also trained the classifier on *visual* trials and tested on *tactile* trials, which produced similar but weaker results (see Inline Supplementary Fig 1). This asymmetry in the direction of generalisation is likely due to variation in signal-to-noise between datasets (Hurk and Beeck, 2019), and may reflect the greater temporal uncertainty in the videos which increases the trial-by-trial and between-participant variability in the visual domain.

452 We also tested for a difference between the groups at each timepoint (Fig 2c.). This demonstrated
453 strong evidence for a difference between the high tactile empathy and low tactile empathy groups in
454 terms of the degree to which between-modality decoding was present. This is an additional statistical
455 verification of the presence of *between-modality* decoding in the high tactile empathy group and the
456 lack of such decoding in the low tactile empathy group.



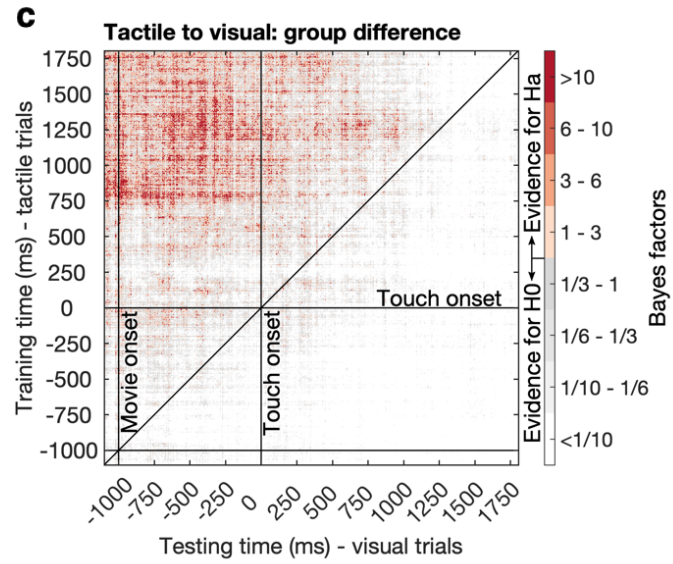
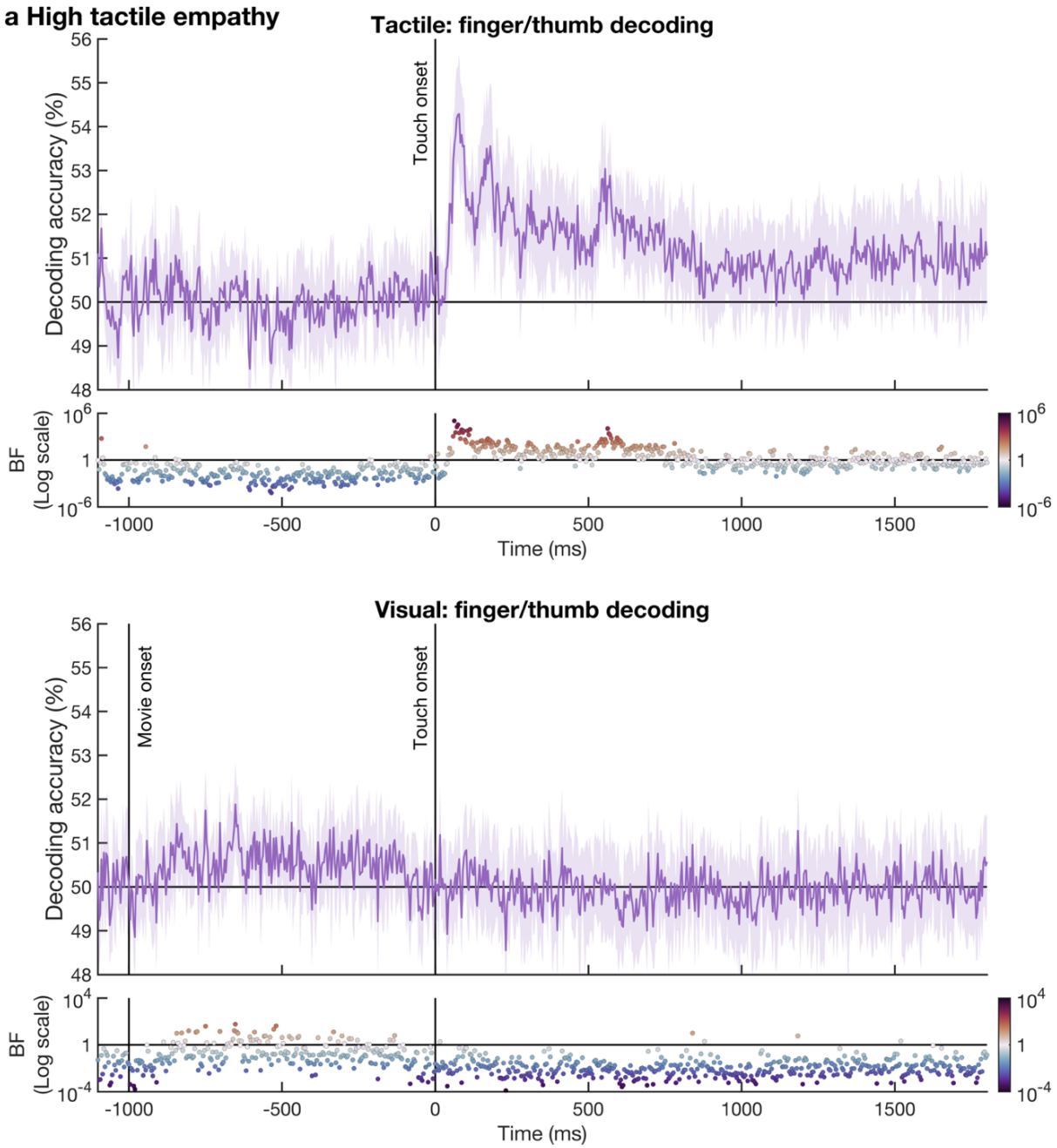


Figure 2. Strong evidence in individuals with high tactile empathy for *between-modality* decoding when training on *tactile* trials and testing on *visual* trials. Left plots: Mean classification accuracy for each train-test timepoint distinguishing touch to the little finger versus the thumb in the **(a)** high (n = 16) and **(b)** low (n = 18) tactile empathy groups. Right plots: Corresponding Bayes Factors. **(a)** Above-chance decoding (>50%; purple) when training on the late *tactile* signal (~400:1800ms) and testing on the early *visual* signal (approx. -1000:750ms), with the remainder of timepoint combinations showing chance-decoding (white). BFs show the strongest evidence (red) when training on ~750ms after touch onset in the tactile signal and between approximately -1000 and -250ms in the visual signal. **(b)** Above-chance decoding (>50%; purple) is observed sparingly, with mostly at-chance decoding (white). BFs

provide very little anecdotal-moderate evidence (light orange) for cross-decoding, with mostly strong evidence for chance-decoding (white). (**c**) Comparison at each timepoint of the *between-modality* classification accuracy between groups. BFs show the strongest evidence (red) for a difference between the groups when training on ~750ms after touch onset in the tactile signal and between approximately -1000 and -250ms in the visual signal. There is also evidence for a difference between the groups later in the visual signal until ~1000ms. For visualisation, all BFs >10 are plotted red, but the maximum BF is >2000.

Within-modality decoding

To assess whether a classifier can successfully extract neural signatures distinguishing touch to the little finger versus thumb *within each modality*, and at what time, we trained and tested a classifier using only the tactile *or* visual data. 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 was maintained throughout the trial (Fig. 3ab top panels). This shows the remarkable sensitivity of these methods, considering the proximity of finger representations in somatosensory cortex (Kuehn et al., 2014). For *visual* stimuli, decoding of touch location was also present but much more subtle, reflecting the indirect information about touch (watching a video) and temporal variability when making inferences about an unfolding touch event. For visual stimuli, the high tactile empathy group showed some above-chance decoding early in the trial (~170ms after video start until ~130ms before the touch onset; Fig. 3a bottom panel) suggesting 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. The low tactile empathy group showed some above-chance decoding for a short period ~160ms after video onset, and again later in the trial between ~260-400ms during the touch (Fig. 3b bottom panel).


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

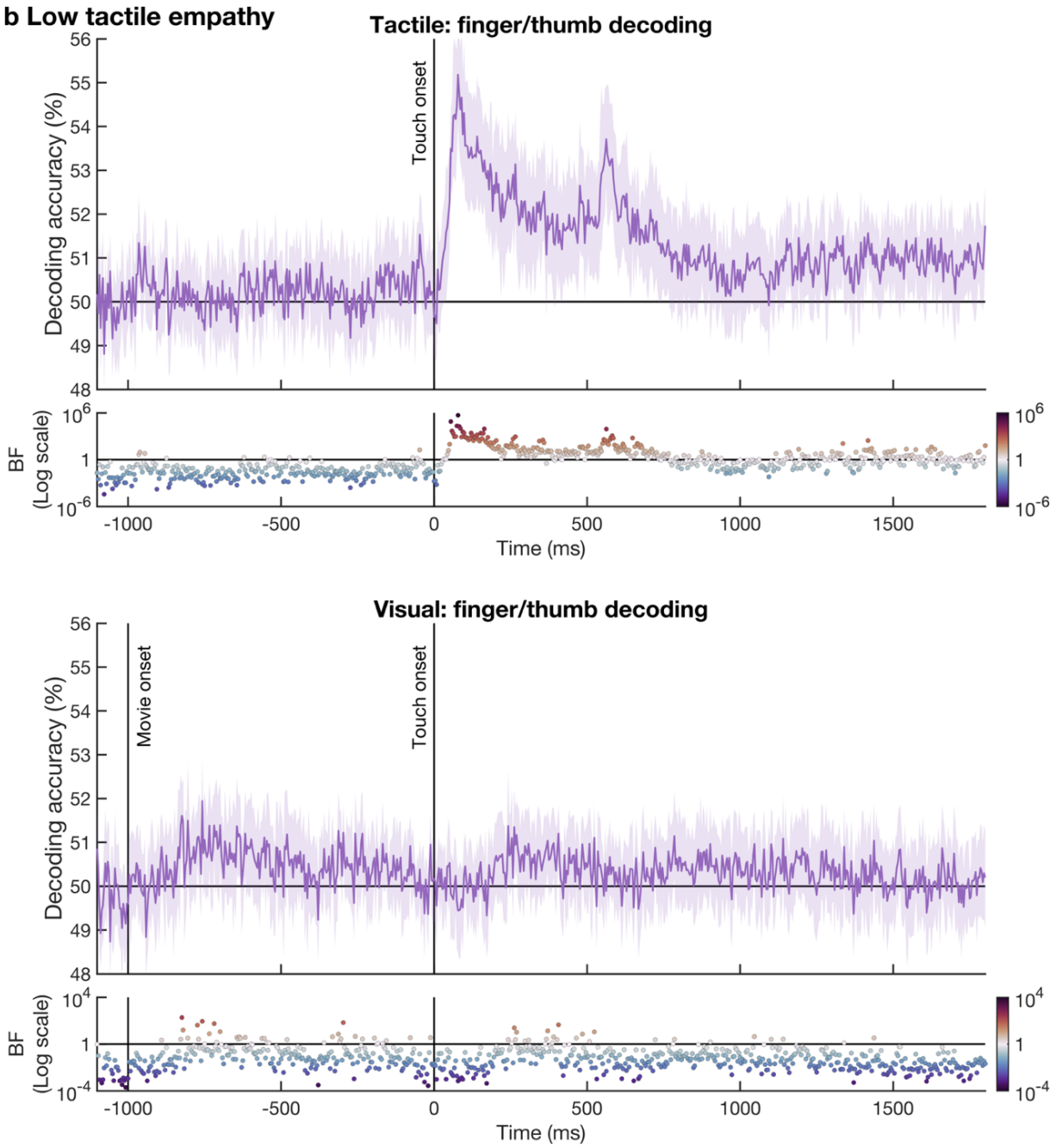


Figure 3. Within-modality decoding for the tactile (top) and visual (bottom) modalities. Mean classification accuracy over time for the **(a)** high (n = 16) and **(b)** low (n = 18) tactile empathy groups. Tactile decoding plots (top) show an initial baseline period of 1100ms (100ms baseline + 1000ms 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 (red: above-chance decoding) or the null (blue: chance decoding); note the different colour bar scales for top and bottom panels. For both groups, the location of touch 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, location of touch can be decoded for *visual* trials from ~160ms after the start of the video and again later in the trial between ~260-400ms during the touch (touch is 0-500ms).

Discussion

We tested the prediction from simulation theories of tactile empathy that seeing touch evokes similar representations as feeling touch, and explored the link with variation in tactile empathy, using a multivariate decoding approach. Our main finding was that only in people with high tactile empathy are representations of the specific location of touch shared *between* modalities. The chance-level decoding between modalities for the low tactile empathy group, and the strong evidence for a difference between the groups, provide a link between shared touch representations and tactile empathy. In the high tactile empathy group, late tactile patterns overlapped with early visual patterns: seeing touch activated information that occurred 400ms after being touched – therefore presumably reflecting high-level tactile information. The *within-modality* tactile decoding results demonstrate that information about which finger was touched is already present very early on (~45ms onwards) for both groups, but this is *not* what is instantiated when we see touch.

Some simulation theories propose that we understand other's sensations by first representing the observed event in our own relevant perceptual areas. This representation is then 'directly matched' against sensations we could experience first-hand. Such an automatic process allows for passive 'resonating' with another person (e.g., Iacoboni et al., 1999; Rizzolatti et al., 2001; Rizzolatti and Sinigaglia, 2016). Other simulation theories argue that tactile empathy could be better explained as a prediction process (for a review see Bach and Schenke, 2017). Such 'predictive coding' accounts propose that social interactions, including vicarious touch, are hypothesis driven, such that an assumption about the external world is transformed into predictions about the expected perceptual consequences of the observed event. Prediction errors about an observed touch event without direct tactile input can be 'explained away' by activity in the somatosensory cortex (Bach and Schenke, 2017; Ishida et al., 2015). Both these accounts propose that seeing touch should evoke corresponding *sensory* representations (see also Banissy and Ward, 2007; Bufalari and Ionta, 2013; Keysers and Gazzola, 2009; Schaefer et al., 2009). This predicts that the same information that is present early on when we are touched should also be instantiated when we see someone else being touched. In our experiment, this would mean that *between-modalit*y decoding should involve early tactile information appearing within the visual patterns.

Some aspects of our *between-modality* decoding results are consistent with simulation theories. Tactile information did appear in visual trials before the stick touched the hand in our high tactile empathy

group. This suggests that this information is involved in predicting the consequences of an upcoming touch. When the touch actually occurred in the video, the *between-modality* decoding dropped to chance. This is consistent with a predictive coding account whereby the lack of predicted tactile stimulation then modulates the neural response. However, our Bayesian analysis provides strong evidence that the early tactile information (<400ms after tactile stimulation) *does not* generalise to the visual representation. This indicates that any simulation or prediction of seen touch operates at a higher or more abstract level than previously thought (see also Kilteni et al., 2021). Previous univariate EEG studies found both early (45ms) and late (200-600ms) somatosensory ERP modulations when participants saw and felt touch simultaneously (relative to a no-touch visual stimulus + touch), which has been taken as evidence that shared representations are already present at very early processing stages (Adler et al., 2016; Adler and Gillmeister, 2019; Bufalari et al., 2007; Deschrijver et al., 2016; Martínez-Jauand et al., 2012). Having simultaneous seen and felt touch, however, means it is difficult to disentangle multisensory integration modulations from shared neural representations. Our results suggest that only the later ERP effects are likely to reflect shared touch representations, and that this would depend on whether the participant has high or low tactile empathy. Our findings have important implications for simulation theories as the data suggest that empathising with tactile sensations does not rely on the activation of a low-level sensory representation of the touch.

The presence of shared representations at a high-level processing stage might explain why high tactile empathy individuals report vicarious touch only in certain contexts, such as when specifically attending to experimental videos of touch. In contrast, mirror-touch synaesthetes feel other people's sensations in non-experimental contexts (e.g., watching a movie, seeing someone being touched). Previous studies report that mirror-touch synaesthetes' vicarious sensations are exteroceptive rather than interoceptive (e.g., feeling touch or pressure rather than tingling: Banissy et al., 2009; Ward et al., 2018). It is therefore possible that for mirror-touch synaesthetes, seeing someone else being touched evokes comparatively earlier (more low-level or sensory) tactile representations. Our experimental paradigm allows future investigation into the temporal characteristics of neural representations in mirror-touch synaesthesia and neurodiverse populations in which self-other processing is altered (e.g., psychopathy, autism, alexithymia or depersonalisation disorder: Bird and Viding, 2014; Gillmeister et al., 2017).

One aspect of our methodology that is crucial to note is that a classifier can pick up not only the effect of interest (here, which finger was touched), but also any other feature that differs between the conditions of interest (e.g., mental labelling, low-level stimulus features, systematic eye movements: Alizadeh et al., 2017; Woolgar et al., 2014). If participants were mentally labelling trials as "little finger" or "thumb", for example, this could be an alternative explanation for our *between-modality* decoding. In our task, however, labelling each trial as such would interfere with completing the task (cumulative counting of targets to each finger across trials), and the target trials were excluded from analyses. Further, it is unclear why any such labelling strategy would differ between people with high and low tactile empathy. Our careful experimental design also controls for external touch side, low-level visual features and systematic eye-movements (by having touch side orthogonal to the decoded feature of which finger was touched). This, in combination with strong evidence for shared representations only in the high tactile empathy group, supports the interpretation that our *between-modality* decoding reflects overlap in neural patterns that are specific to touch representation.

Another specific issue related to using multivariate decoding is whether one is using it for *interpretation* or trying to *maximise prediction*. Here, we are looking for evidence that a neural pattern instantiated when feeling touch is also present when viewing touch: using decoding for interpretation. Thus, any decoding above chance shows there is structure in the data that allows for categorical distinction between conditions (Hebart and Baker, 2018). In this context, the absolute decoding values are less important. We used minimal pre-processing (e.g., no filtering, trial rejection, trial averaging, channel-selection) and thus effectively ran our analysis on near-raw data. This ensures our outcomes do not rely on specific pre-processing choices, but also means the data are noisier, which can result in lower decoding accuracies (Grootswagers et al., 2017). In addition, our careful control of the video stimuli ensuring large visual signals such as external touch side cannot drive the classifier means the remaining signals that reflect which finger was touched are quite subtle. This, combined with temporal variability between trials and participants when observing the visually unfolding touch event, make it unlikely that one would see high decoding accuracies in the visual trials. Our *between-modality* decoding accuracies are low (~52%; recall that the stimuli are coming through completely different sensory streams), but this is not indicative of effect size (Combrisson and Jerbi, 2015; Hebart and Baker, 2018). In fact, the strength of the evidence from our Bayes Factors (see Fig. 2) gives a much better indication of the robustness of the effect: the classifier was reliably able to pick up a similarity in neural patterns between seeing and feeling touch in people with high tactile empathy.

In conclusion, our results increase the understanding of how tactile empathy is processed in the brain by showing that seeing another person being touched can activate representations overlapping with those evoked by feeling touch directly. Such shared representations were only observed in people who reported feeling touch when seeing videos of touch, suggesting a link between visually evoked touch representation and variation in tactile empathy. The timecourse of our findings indicates that observing an approaching touch to another person evokes a high-level abstract touch representation, rather than the early somatosensory representation proposed by current simulation theories. This provides the first direct evidence that in some people, a high-level tactile neural representation is instantiated when watching someone else being touched.

Author Contributions (CRediT):

SS: Conceptualization, Methodology, Software, Investigation, Data Curation, Formal analysis, Visualization, Writing – Original Draft, Writing – Review & Editing, Project administration. **DM**: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – Review & Editing. **RZ**: Conceptualization, Writing – Review & Editing, Supervision, **ANR**: Conceptualisation, Methodology, Writing – Review & Editing, Supervision.

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