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Towards thermal imagery-based brain-computer interfaces

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ABSTRACT: Mental task-based brain-computer interfaces (BCIs) enable users to control a system by voluntarily modulating their brain activity without overt movement. Research in the field has focused mainly on motor imagery, whereas tactile imagery, defined as the imagination of tactile stimuli on the skin, remains comparatively underexplored. Although pressure and vibratory imagery have received growing attention, other modalities such as thermal imagery remain largely neglected, despite their potential clinical relevance. In this EEG-based BCI study, healthy participants learned to control a BCI by imagining a warm sensation in the right hand, representing, to our knowledge, the first thermal imagery-based BCI user training. To facilitate mental representation, participants received visual, thermal, or combined visuothermal instructions. Thermal imagery elicited event-related desynchronization, primarily over left sensorimotor regions, and online performance improved significantly across runs. Comparisons between instruction modalities suggested trends favoring visual and thermal guidance. Together, these findings support the feasibility of thermal imagery as a promising alternative control paradigm for BCI applications.

INTRODUCTION

Brain-computer interfaces (BCI) are technologies that enable the control of external devices by translating central nervous system activity into control commands [1]. BCIs have been investigated for both clinical and non-clinical applications [2]. One of the most widely used paradigms to control a BCI is kinesthetic motor imagery (KMI), which involves imagining moving a limb without performing the action [3] combined with imagining sensations associated with its execution (e.g., muscle tension and proprioceptive sensations). However, current BCI paradigms remain insufficiently reliable for widespread deployment beyond research settings. One of the major challenges remains the phenomenon of BCI inefficiency, where BCI control based on classical paradigms such as KMI fails in approximately 15-30% of users. Previous work suggests that this problem may, at least in part, stem from limitations in the design of current BCI systems [4, 5].

Alternative BCI paradigms have been proposed to address the difficulties participants may encounter when training with conventional approaches. Unlike KMI, which relies on imagined movement, tactile imagery (TI) relies on the imagination of tactile stimulation on the skin, most commonly pressure and vibratory stimulation, and several studies have already demonstrated its feasibility in BCI paradigms [6–9]. KMI and TI both rely on oscillatory brain dynamics, commonly quantified via event-related desynchronization/synchronization (ERD/ERS) in sensorimotor rhythms [6–8], reflecting decreases (ERD) or increases (ERS) in oscillatory power relative to a baseline period. Both KMI and TI elicit ERD in the alpha (8-13Hz) and beta (13-30Hz) bands, with TI showing particularly pronounced alpha-range modulations [7, 8] and statistical comparisons between the two revealing significant differences mainly in that frequency band. TI has been shown to exhibit neural activation patterns closely resembling those observed during real tactile stimulation [8, 10], whereas KMI recruits largely overlapping neural networks with those involved in voluntary movement.

Within the context of TI, the existing literature mostly focuses on the imagery of pressure or vibratory tactile stimulation. Other modalities, such as cold or heat imagination, to the best of our knowledge, have received no attention despite their potential relevance, notably for clinical applications. Indeed, following a stroke, approximately 50% of patients exhibit impairment affecting not only motor but also sensory functions such as pressure, touch, pain, and temperature perception. It is not yet clear which somatosensory abilities are the most frequently impacted [11, 12]. Given that TI has been shown to recruit sensory-related regions [6], it may represent a relevant approach for rehabilitation protocols, particularly when combined with congruent sensory feedback to facilitate neuroplasticity mechanisms [13]. In this context, thermal imagery (ThI) appears to be a potentially relevant approach for the rehabilitation of sensory deficits. Moreover, similarly to pressure or vibratory TI, which shares neural activation patterns with actual tactile stimulation [8], it can be hypothesized that ThI activates neural networks comparable to those recruited during real thermal stimulation. This is of particular interest given that thermal stimulation has been shown to facilitate recovery in post-stroke patients [14]. Furthermore, exploring alternative forms of mental imagery may enable individuals for whom classical paradigms, such as KMI, are ineffective

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to identify better-suited strategies. Such diversification of paradigms could contribute to mitigating the issue of BCI inefficiency by broadening the range of viable control strategies across users. However, BCI user training, during which BCI users learn to control their brain activity based on ThI, has not yet been explored, despite also being an imagery-based approach relying on the modulation of neural rhythms.

To facilitate the reconstruction of sensory representations, some studies have introduced a brief stimulation phase to facilitate participants' tasks, particularly in pressure and vibratory tactile imagery [9, 15]. These stimuli, delivered either at the beginning of each trial [15] or before the imagery condition [9], had the purpose of helping participants better reproduce the target sensations during the imagery task. However, the effect of different instruction modalities on brain activity or user experience has not been reported. We hypothesise that for ThI, the modality of instruction will significantly impact the resulting change in brain activity and participants' performance.

In this context, the present experiment aimed to evaluate a novel BCI paradigm based on ThI by addressing two main questions: (i) Can ThI be used to control a BCI, and can its efficiency be enhanced through user training? (ii) Does the type of instruction significantly influence BCI performance?

MATERIALS AND METHODS

To examine the effect of the instruction modality presented at the beginning of each imagery trial, participants completed three different instruction conditions: visual, thermal and visuothermal, presented in a counterbalanced order across participants. To assess training effects within each condition, participants first performed one ThI run without feedback, followed by two runs with feedback. For each condition and at the end of the session, questionnaires were used to collect participants' subjective evaluations.

Participants:

Twenty healthy right-handed participants (13 women, 7 men, age 28.2 $\pm$ 5.7 years) took part in the experiment. All participants were fluent in either French or English, had normal or corrected-to-normal vision and hearing, and reported no history of neurological or psychiatric disorders. Participants were excluded if they reported traumatic brain injury, epilepsy, or chronic cardiovascular/metabolic diseases. All participants provided written informed consent before the experiment. The study protocol was reviewed and approved by a national ethical committee (Coerle n°2025-62). Each participant received a compensation of 20 euros for their participation.

Experimental protocol:

The experiment lasted approximately two hours, including setup, calibration, and cleaning procedures. The actual recording time was about one hour. The experimental plan is displayed in Figure 1. Written instructions

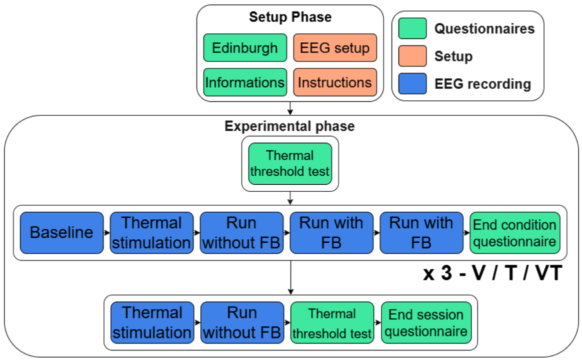

Figure 1: Experimental protocol. The three conditions i.e., visual (V), thermal (T), visuothermal (VT) were presented in a counterbalanced order across participants.

were provided to each participant to ensure consistency and reproducibility of the experiment. Upon arrival, participants completed demographic and Edinburgh Handedness Inventory handedness questionnaires (see section Questionnaires). To immerse participants in a realistic scenario and provide embodied feedback, we used a virtual environment displayed in the VR headset. The scene was a neutral room with a table aligned with the real table in front of which the participants sat. On the table was an animated bonfire used for instruction and feedback. The VR headset was rigidly mounted to a custom headrest system. This setup both reduced head movement-related artifacts and limited small electrode shifts that can occur when the headset is removed between conditions. Height and depth of the VR headset were adjusted for comfort and a stable fit.

At the beginning of the experiment, a thermal threshold test based on the method of levels (LV) paradigm from [16] was conducted to determine the minimal temperature participants were able to detect. For each condition, participants received a series of twenty non-painful thermal stimuli. They were instructed to remain still and focus on the perceived sensations. Then, participants completed one run of ThI without feedback, followed by two runs with feedback. Each run consisted of 20 trials and followed the same structure, 2 s of rest, during which participants were instructed to relax and remain still, 2 s of the condition specific instruction, 5 s of ThI performed with or without feedback including 1 s of cue indicating the onset of the imagery period and a final rest period randomly varying between 1 and 2 s. The first run without feedback of each condition served as a calibration phase. ERDS features extracted during the imagery periods of this run were used to compute the feedback delivered in the following runs with feedback. After completing the two runs with feedback, participants filled in a questionnaire. Then after completing the three conditions, participants performed an additional thermal stimulation run and an additional run of ThI without feedback, followed by a final thermal threshold test and an end-of-session questionnaire.

Different instruction modalities were used across both runs, with and without feedback, depending on the condi-

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tion. The order of the conditions was pseudo-randomized and counterbalanced across participants. In each condition, participants were asked to imagine a sensation of warmth according to the instructions provided as follows:

- Visual (V) – visual animation in VR of a campfire burning displayed between two virtual arms. Participants were asked to imagine a feeling of heat on the back of their hand as if the campfire were real.
- Thermal (T) – thermal stimulation delivered on the back of the hand (see Section Thermal stimulation). Participants were asked to imagine the same sensation of heat that they felt during the stimulus.
- Visuothermal (VT) – a combination of visual and thermal instructions. Participants were asked to imagine the same sensation of heat on the back of their hand that they felt during the stimulus, and as if the campfire were real.

Thermal stimulation:
To deliver non-painful thermal stimulation on the back of the participants' hands, a device was designed based on the system developed in [17], with a HS-85MG servo motor. The device integrates a Force-Sensing Resistor to ensure a controlled and consistent pressure across all participants. Temperature regulation is achieved using a thermistor. The temperature applied to each participant was individualized and based on their thermal threshold test results (see Section Experimental protocol). Specifically, the absolute value of the threshold measured at the beginning of the experiment was used, and 10 °C were added to determine the stimulation temperature to ensure that the thermal stimuli were detectable but not painful. Participants were systematically asked to confirm whether the stimulus was not painful, both verbally and through post-task questionnaires.

EEG Recordings:
The EEG data was recorded with 30 active electrodes, using a g.USBAmp EEG amplifier (g.tec, Austria). The electrodes were placed over the sensorimotor cortex (at locations Fp1, Fp2, F3, F4, FC5, FC6, FC3, FC4, FC1, FC2, FCz, T7, T8, C5, C6, C3, C4, C1, C2, Cz, CP5, CP6, CP3, CP4, CP1, CP2, CPz, P3, P4 and Oz in the 10-20 system), referenced to the left earlobe and grounded to AFz. Data was sampled at 512 Hz and processed using OpenViBE 3.6.0 [18]. Two participants were excluded from further analysis due to excessive noise in the recorded EEG data.

Online Feedback:
During runs with and without feedback, the online data used to compute ERDS was processed as follows. We first selected the signal from electrodes CP3, C1, C5, and P3, which was then filtered between 8 and 30 Hz. We then applied a Laplacian filter centered on CP3, which was chosen due to its location over the somatosensory cortex. Based on previous literature indicating that TI elicit activation in the somatosensory cortex [6–9], this approach was chosen to enhance spatial resolution [19].

During the resting phases of each trial (2 s), the output signal was epoched using a 1 s window, sliding every 0.1 s. For each epoch, the signal was squared and then time-averaged to get the band power. Outlier epochs outside 3 standard deviations were removed, and the remaining epochs were averaged and used as the Rest value to compute the ERDS of the following ThI task. During the ThI periods of each trial, the output signal from the Laplacian filter was epoched using a 250 ms window every 250 ms. The signal of each epoch was squared and then time-averaged to estimate the band power. For every epoch, this average was used as the Task value to compute the online ERDS as follows:

$$ERDS_{online} = \frac{Task - Rest}{Rest} * 100 \tag{1}$$

During the run without feedback of each condition, a calibration score $ERDS_{calib}$ was computed. At the end of the run, all the $ERDS_{online}$ values calculated during the run were sorted in ascending order, and the value at the 30th percentile was selected as $ERDS_{calib}$. During the runs with feedback, the $ERDS_{calib}$ obtained from the run without feedback was used to compute an ERDS score (S_{ERDS}) based on the $ERDS_{online}$ measured during the task as follows:

$$S_{ERDS} = \frac{ERDS_{online}}{ERDS_{calib}} * 100 \tag{2}$$

The S_{ERDS} was then discretized to define the participant's performance score and determine the intensity of the feedback provided to the participant (see Figure 2), with level 0 displaying no intensity and 3 displaying maximum intensity.

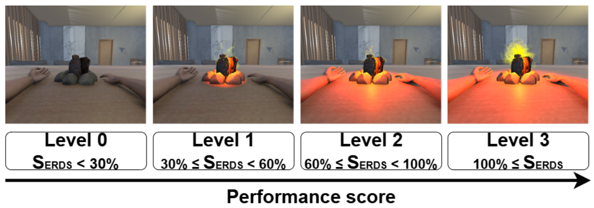

Figure 2: Visual feedback provided during the runs based on the user performance S_{ERDS}

Questionnaires:
First, we assessed participant characteristics that could potentially influence the results using two questionnaires. These include the evaluation of lateralization through the Edinburgh questionnaire [20], as well as the collection of demographic variables. We also examined the user experience associated with ThI for BCI control at the end of each condition and the session.

Analysis:
First, we investigated whether participants' performance improved over time across the two runs with feedback of each condition, and whether differences were observed between the condition-specific instructions. We used a two-way repeated-measures ANOVA on the averaged

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S_{ERDS} measured, with *Condition* (levels: Visual, Thermal, Visuothermal) and *Run* (levels: Run 1 and Run 2) as independent variables. Post-hoc pairwise comparisons were performed using Holm correction to account for multiple comparisons. Outliers can strongly influence statistical tests and may artificially affect the significance of the results. To ensure more reliable statistical analysis, participants presenting outlier values according to the predefined criteria were excluded from the analysis. For each run with feedback of each condition, participants' averaged performance was used to identify outliers, defined as the values outside two standard deviations from the mean of the run. Participants who exhibited ERDS outliers in three or more of the six total runs were excluded from statistical analysis. In total, one participant was excluded from this analysis. Then, to investigate whether participants' performance improved over the course of the experiment during runs without feedback, we conducted a one-way (1 x 4) repeated-measures ANOVA on the averaged S_{ERDS} measured during the four runs without feedback, with *Run* (levels: Run 1, Run 2, Run 3, and Run 4) as a within-subject factor. Post-hoc pairwise comparisons were performed using Holm correction to account for multiple comparisons. To examine the systematic evolution of the dependent variable across the four runs, polynomial contrasts were applied to the *Run* factor. This approach allowed us to specifically test for linear, quadratic, and cubic trends in the repeated measures. Inspection of the coefficient allowed us to verify if this trend was negative, as expected if participants improved their performance over the course of the experiment. For each run without feedback, participants' averaged performance was used to identify outliers, defined as the values outside two standard deviations from the mean of the run. Participants who exhibited ERDS outliers in two or more of the four runs were excluded from statistical analysis. In total, three participants were excluded from this analysis.

RESULTS

Two-way repeated-measures ANOVA on participants' performance during the two runs with feedback showed a significant effect of *Condition* (see Figure 3). Since Mauchly's test of sphericity was significant for *Condition*, the Greenhouse-Geisser correction was used ($F(1.296, 20.742) = 4.124$, $p_{\text{corrected}} = 0.046$, $\eta^2 = 0.106$). Among the 17 participants, one participant showed ERS on average in both runs of the visuothermal condition as well as in one run of the visual and thermal conditions. Two other participants showed ERS in one run of the visuothermal condition. The remaining participants showed ERD on average during all the runs. In addition, values are in average more negative in the visual ($M = -27.087$, $SD = 16.665$) and thermal ($M = -24.718$, $SD = 19.355$) conditions compared to visuothermal ($M = -19.571$, $SD = 21.308$). Post-hoc comparisons (Holm-corrected) revealed a tendency between thermal and visuothermal conditions ($p = 0.070$, $d = -0.247$) and between visual and visuothermal conditions ($p = 0.098$, $d = -0.360$). A marginal effect was found for *Run* ($F(1,16) = 3.234$, $p = 0.091$, $\eta^2 = 0.025$), with Run 2 ($M = -25.329$, $SD = 18.805$) showing more negative values than Run 1 ($M = -22.256$, $SD = 18.294$). However, no significant effect was found for the interaction *Condition* × *Run* ($F(2,32) = 1.117$, $p = 0.336$, $\eta^2 = 0.022$). Participants were divided based on ERDS magnitude of the two runs averaged. Strong responders (ERDS < -20%) represented 44% of the participants (n = 8), moderate responders (-20% < ERDS < -10%) accounted for 33% (n = 6) and low responders (-10% < ERDS < 0%) accounted for 22% (n = 4).

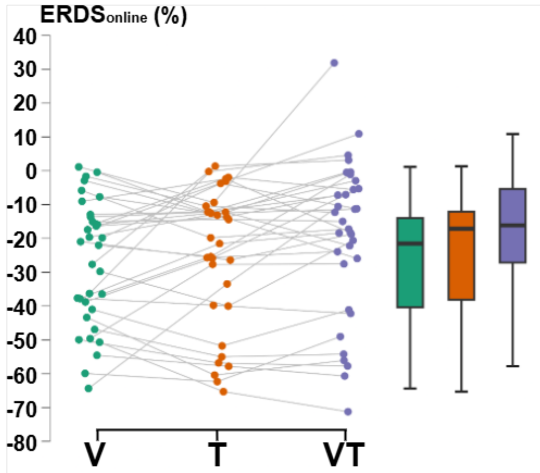

Figure 3: Averaged $ERDS_{online}$ during runs with feedback averaged over all participants for visual (V), thermal (T) and visuothermal (VT) conditions.

The analysis on the averaged $ERDS_{online}$ measured during the runs without feedback (see Figure 4) indicated that *Run* had a significant effect ($F(3,42) = 3.315$, $p = 0.034$, $\eta^2 = 0.211$). ERD became progressively more negative from Run 1 ($M = -6.518$, $SD = 16.701$) to Run 3 ($M = -16.470$, $SD = 16.214$), then partially rebounded in Run 4 ($M = -13.693$, $SD = 15.342$). From the first run, desynchronization is apparent, with most values presenting negative synchronization changes. Post-hoc comparisons (Holm-corrected) revealed no further significant effect between runs.
In order to examine whether the effect of *Run* followed a specific trend, we conducted a polynomial contrast after the ANOVA. The results revealed a moderate linear trend ($t(17) = -2.169$, $d = -0.334$, $p = 0.051$), indicating that ERD decreased linearly across runs ($Estimate = -5.505$, $SE = 2.538$). The quadratic trend showed a similar trend ($t(17) = 1.834$, $p = 0.092$, $d = 0.293$), suggesting weak quadratic shape ($Estimate = 4.818$, $SE = 2.627$). The cubic trend was not significant ($t(17) = 0.212$, $p = 0.835$, $d = 0.020$), indicating no higher-order trend. Participants were grouped according to the ERDS magnitude observed during the run. Strong responders (ERDS < -20%) represented 33% of the participants (n = 6), mod-

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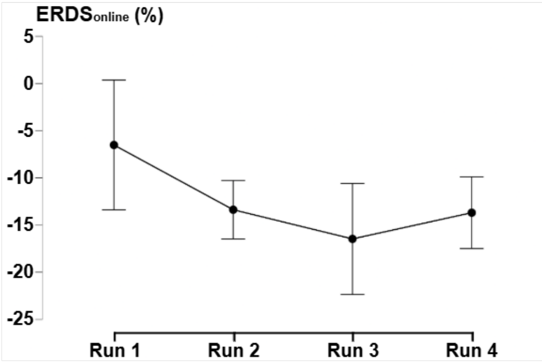

Figure 4: Evolution of the average $ERDS_{online}$ measured during runs without feedback, averaged over all participants, with a 95% confidence interval.

erate responders (-20% < ERDS < -10%) accounted for 22% (n = 4), and low responders (-10% < ERDS < 0%) accounted for 22% (n = 4). The remaining 22% (n = 4) were classified as non-responders (ERDS > 0%), exhibiting ERS.

DISCUSSION

The present study examined the feasibility of using thermal imagery and whether participants could learn to regulate their own brain activity through this approach. To this end, participants were immersed in a virtual environment with a small bonfire placed in front of them and instructed to imagine non-harmful heat sensations on their right hand under three different instruction conditions: visual (animated bonfire), thermal (Peltier-based stimulation), or visuothermal (combining both). Then, they received visual feedback on their imagery performance through the bonfire animation. The following sections discuss the study's research questions presented in the Introduction.

Can somatosensory imagery be used to control a BCI and its efficiency be enhanced through user training?:
Our first objective was to determine whether ThI can elicit reliable neurophysiological responses suitable for BCI control. Using ERDS computed online during the imagery phase, we observed ERD over the left sensorimotor cortex at electrode CP3, during both runs with and without feedback. This pattern is consistent with findings in TI studies, where imagining pressure or vibratory tactile sensations induced lateralized ERD in the α and β bands [6–8] in the sensorimotor cortex. Beyond previous TI studies, our observation of an online ERD over the left sensorimotor cortex during right-hand thermal imagery is consistent with EEG evidence showing contralateral alpha desynchronization during tactile imagery, especially over central electrodes, and with source-imaging and fMRI studies [10] indicating that tactile imagery recruits contralateral sensorimotor and somatosensory regions with partial overlap with real tactile stimulation. These results support the feasibility of using ThI as a control strategy for BCI applications. Additionally, a comparable proportion of low or non-responders was observed, which is in line with the findings in the literature on motor imagery [4]. We then examined whether participants improved over time. When looking at the runs without feedback, we observed a significant improvement in participants' performance over the course of the experiment, even in the absence of feedback. However, the absence of a control group prevents us from concluding whether performance improvements are due to participant learning or to other factors, such as repeated exposure to thermal stimuli, which could also activate the somatosensory cortex in a similar way to ThI, as it has been shown with TI and tactile stimuli [6, 8]. No significant improvement but a tendency toward improvement was observed across the runs with feedback within each condition. One possible explanation is that the runs were conducted in close temporal succession, limiting the measurable impact of the training between two runs. These findings may indicate feedback-independent learning processes unfolding during BCI user training. It is also possible that performance improves naturally with repeated trials. We will test this hypothesis in a future double-blind study including a control group receiving sham feedback.

Does the type of instruction significantly affect BCI performance?:
During the experiment, we included an instruction phase preceding the imagery period aimed at helping and preparing participants to imagine a warm sensation, similar to Yao et al., 2018 [15]. We investigated whether significant differences exist between visual, haptic, and visuothermal modalities, with the goal of better guiding participants in performing the task. Analysis of the online performance revealed a significant difference between conditions, with a trend between the visuothermal instruction and the other two. A visual inspection of the results suggests a larger ERD for visual and thermal conditions compared to the visuothermal condition. This pattern may be consistent with previous findings suggesting that multimodal feedback may not be optimal during the early stages of learning, as novices may have difficulty integrating information from multiple modalities [21]. A similar effect could therefore be expected with multimodal instructions, especially for a combination of visual and thermal instructions, which differed in terms of continuity and discreteness. The spatial placement also differed, as the visual instruction consisted of a campfire presented in front of the participant, whereas the thermal instruction involved a warm stimulus applied to the participant's hand.

Limitations:
Several participants reported experiencing discomfort during the instruction phase of the visuothermal condition. In particular, the lack of coherence between the continuous visual part of the instruction, consisting of a continuous campfire animation, and the thermal part, delivered as a discrete thermal tactile stimulus applied to the back of the hand, was reported by multiple participants. This qualitative feedback will help us design fu-

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ture protocols, in which more coherent visual stimuli will be proposed to better match the sensations perceived and imagined by the participants.

CONCLUSION

In BCI research, TI paradigms remain largely limited to the imagination of pressure or vibratory stimulation, despite the potential relevance of other sensory modalities. To the best of our knowledge, ThI has not previously been investigated as a BCI control strategy, including in user-training paradigms. In the present study, we examined whether imagined warm sensations could be detected from EEG signals, whether performance improved with training over time, and whether it could be enhanced through visual, thermal, or combined visuothermal instructions. Our results demonstrate that a modulation in brain activity is observable based on changes in sensorimotor rhythms in the α–β bands, and could be used to detect whether a participant is performing ThI, potentially serving as a control strategy for BCI. Participants also exhibited significant improvements in online performance across runs without feedback. Although instructions significantly influenced performance at a global level, further analysis did not reveal significant differences between the instruction modalities. However, there was a tendency toward stronger effects with visual and thermal instructions. Overall, this study provides evidence that a novel imagery paradigm using the imagination of warm sensations can be implemented. This may represent a promising direction for clinical applications and individuals who experience difficulties with classical imagery paradigms. Further analysis will investigate whether neural response to a thermal stimulus could predict ThI performance and its potential ability to influence thermal perception in healthy participants.

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