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Pavlovian-based neurofeedback enhances meta-awareness of mind-wandering

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A B S T R A C T

Absorption in mind-wandering (MW) may worsen our mood and can cause psychological disorders. Researchers indicate the possibility that meta-awareness of MW prevents these mal-effects and enhances favorable consequences of MW, such as boosting creativity; thus, meta-awareness has attracted psychological and clinical attention. However, few studies have investigated the nature of meta-awareness of MW, because there has been no method to isolate and operate this ability. Therefore, we propose a new approach to manipulate the ability of meta-awareness. We used Pavlovian conditioning, tying to it an occurrence of MW and a neutral tone sound inducing the meta-awareness of MW. To perform paired presentations of the unconditioned stimulus (neutral tone) and the conditioned stimulus (perception accompanying MW), we detected participants' natural occurrence of MW via electroencephalogram and a machine-learning estimation method. The double-blinded randomized controlled trial with 37 participants found that a single 20-min conditioning session significantly increased the meta-awareness of MW as assessed by behavioral and neuroscientific measures. The core protocol of the proposed method is real-time feedback on participants' neural information, and in that sense, we can refer to it as neurofeedback. However, there are some differences from typical neurofeedback protocols, and we discuss them in this paper. Our novel classical conditioning is expected to contribute to future research on the modulation effect of meta-awareness on MW.

1. Introduction

Mind-wandering (MW) is a phenomenon in which one's attention is directed elsewhere rather than the current task or situation (Smallwood & Schooler, 2006). Though MW occupies a quarter to half of our cognitive state (Killingsworth & Gilbert, 2010; McVay, Kane, & Kwapil, 2009), an excessive tendency to MW is considered to cause some problems. Previous studies have demonstrated that people engaged in more MW tend to exhibit poorer performance on a sustained attention and working memory task (Randall, Oswald, & Beier, 2014), and that occurrence of MW can worsen mood (Killingsworth & Gilbert, 2010; Stawarczyk, Majerus, Van der Linden, & D'Argembeau, 2012). Further, it is discussed that high propensity to let the mind wander causes various mental health problems (Bozhilova, Michelini, Kuntsi, & Asherson, 2018; Ottaviani & Couyoumdjian, 2013; Perkins, Arnone, Smallwood, & Mobbs, 2015). In particular, a looped relation between MW and depression is known; MW is displayed as one of the symptoms of depression, and MW enhances depression (Burg & Michalak, 2011; Deng & Li, 2012; Marchetti, Koster, & De Raedt, 2012). However, as a positive aspect, previous studies have argued that MW contributes to creative thinking by fostering the association of previously unconnected ideas (Williams et al., 2018; Zedelius & Schooler, 2016). Hence, regardless of its negative consequences, looking for ways to quell our MW is not recommended.

Recently, it has been suggested that the meta-awareness of MW mitigates its adverse consequences. The meta-awareness of MW refers to the explicit knowledge that one is/was in a state of MW at that time or just a moment ago (Schooler, Smallwood, Handy, Reichle, & Sayette, 2011). Meanwhile, it also refers to the ability to acquire the meta-awareness of MW (Konjedi & Maleeh, 2017). Often, we let our minds wander without meta-awareness, and then suddenly realize that we are in MW; in other words, we acquire meta-awareness (Seli, Ralph et al., 2017). People who have high (the ability of) meta-awareness of MW easily notice

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their MW. Researchers have also demonstrated that MW with meta-awareness disturbs performance less (McVay et al., 2009; Smallwood, McSpadden and Schooler, 2008) and induces less negative mood (Deng & Li, 2012; Konjedi & Maleeh, 2017) than without it. Therefore, research into the meta-awareness of MW can substantially contribute to the elucidation of the relation between MW and mental health.

However, few studies have investigated its nature and the moderating function, because of a lack of methods of isolating and intentionally operating one's meta-awareness ability. Some papers have reported conditions that enhance meta-awareness: Zedelius, Broadway, and Schooler (2015) demonstrated that people are more frequently aware of and report more MW when accurate MW reporting is motivated by money; also, meta-awareness decreases when verbal working memory is suppressed and vice versa (Bastian et al., 2017). However, these two studies found only task settings to be controlling the meta-awareness of MW during the task; thus, we need a technique that enhances meta-awareness ability per se, irrespective of context. Mindfulness-based intervention (MBI), which might be the only way to enhance meta-awareness ability by practicing being aware of and observing one's MW (Konjedi & Maleeh, 2017; Teasdale et al., 2000; Vago, 2014), is not suitable to investigate the nature of meta-awareness of MW, because it operates diverse personal traits simultaneously, such as attention regulation, emotion regulation, and self-awareness (Tang, Hölzel, & Posner, 2015).

Here, we thus propose a new approach to manipulating meta-awareness ability. We used classical (Pavlovian, respondent) conditioning that let participants briefly suspend their MWs when they occurred by directing their attention externally and thus induced the awareness of MW. While it is difficult to notice MW during its occurrence, meta-awareness is considered to be regained when an MW episode ends (Schooler et al., 2011; Smallwood, 2013). Therefore, if MW is suspended whenever the mind starts to wander, people are expected to acquire a high tendency to be meta-aware of MW at that time. Classical conditioning, which makes the occurrence of MW elicit its momentary suspension, could create such a state and thus enhance MW meta-awareness ability.

In the proposed classical conditioning, the conditioned stimulus (CS) is the perception accompanying an occurrence of MW, and we use an emotionally neutral tone (not noisy, pure sound) as the unconditioned stimulus (US) and externally directed attention as the unconditioned response (UR). The decoupling hypothesis (Handy & Kam, 2015; Smallwood & Schooler, 2006) explains MW as the state where the cognitive process is engaged in internal information (e.g., memory) instead of the external environment (e.g. vision or sound). The presentation of a salient sound decouples the cognitive process from internal information and recouples it to the external stimulus. We consider this decoupling-and-recoupling process via the salient sound to constitute an intrinsic physiological response, and thus to satisfy the requirements as US and UR.

However, a large problem obstructs the implementation of this conditioning protocol: the difficulty of the paired presentation of US following CS, because CS, that is, the occurrence of MW, is unpresentable by an experimenter. To solve this problem, we detected the natural occurrence of MW in participants via the electroencephalogram (EEG) and machine-learning estimation method and presented US to participants. Previous studies explored EEG features relating to MW intensity and found the power in some frequency bands including theta (Bozhilova, Cooper, Kuntsi, Asherson, & Michelini, 2020; Braboszcz & Delorme, 2011; Jin, Borst, & van Vugt, 2019; Son et al., 2019; van Son et al., 2019), alpha (Arnau et al., 2020; Baldwin et al., 2017; Berkovich-Ohana, Glicksohn, & Goldstein, 2012; Bozhilova et al., 2018; Braboszcz & Delorme, 2011; Compton, Gearinger, & Wild, 2019; Jin et al., 2019), and beta (Berkovich-Ohana et al., 2012; Braboszcz & Delorme, 2011; Son et al., 2019; van Son et al., 2019). Further, researchers have succeeded in constructing machine-learning prediction models for MW using some features of EEG (Dhindsa et al., 2019; Jin et al., 2019; Kawashima & Kumano, 2017). The MW estimator enables us to present the US following the occurrence of MW.

On the first day of the two-day experiment, we collected data with which to detect each participant's MW. Then, on the second day, before and after the short single-phase conditioning, we evaluated the meta-awareness of MW using behavioral and neuroscientific indices. We hypothesized that the proposed conditioning enhances meta-awareness indices more than the random-timing beep presentation and investigated this hypothesis through a double-blinded randomized controlled trial. Our finding suggests that this new type of neurofeedback, applying classical conditioning, allows the isolated operation of meta-awareness of MW and thereby contributes to future research.

The core protocol of the proposed method is real-time feedback on participants' neural information, that is, neurofeedback. However, this Pavlovian-based neurofeedback has many differences from the usual operant-based neurofeedback, which we discuss below.

2. Materials and methods

2.1. Participants

Fifty participants less than 60 years old who had no meditation experience completed the experiment. Of them, we excluded 14 participants (see "Data loss and rejection" for exclusion criteria), and thus analyzed the data from 36 participants. Twenty-three males and four left-handed people were included, and the mean age of participants was 29.25 ± 10.52.

In all, 20 participants were assigned to the Detected Sound (DS; experimental) group and the remaining 16 to the Randomized Sound (RS; control) group. For group assignment, we used stratified randomization, stratifying participants according to sex and assigning them into blocks for each stratum. Each block contained four participants, and, in each, we randomly chose two participants and assigned them to the DS group. The member list of groups was programmatically generated before the start of the experiment for the first subject, and concealed from the experimenter; thus, the experimenter did not know who was assigned to the DS group.

2.2. Outcomes

To investigate the effect of the conditioning, we mainly used the ratio of self-caught MW to probe-caught MW as the behavioral outcome. The probe-caught method is a standard way of measuring the existence or intensity of MW (Weinstein, 2018): Participants perform a task demanding attention focusing, and at times, questions interrupting the ongoing task and asking about their current MW are presented. Researchers consider that we can measure valid MW intensity in this way because probes interrupt participants' MW and let them be aware of their MW (Smallwood, McSpadden, Luus and Schooler, 2008). In the self-caught paradigm, participants perform a task and report MW whenever they notice it. Though sometimes the number of self-caught MWs is also used as the index of the MW trait, it is less popular than the probe-caught number, because self-caught MW reflects not only the MW trait but also the meta-awareness ability. However, the number of self-caught MWs divided by that of the probe-caught MWs as a baseline has been proposed and used

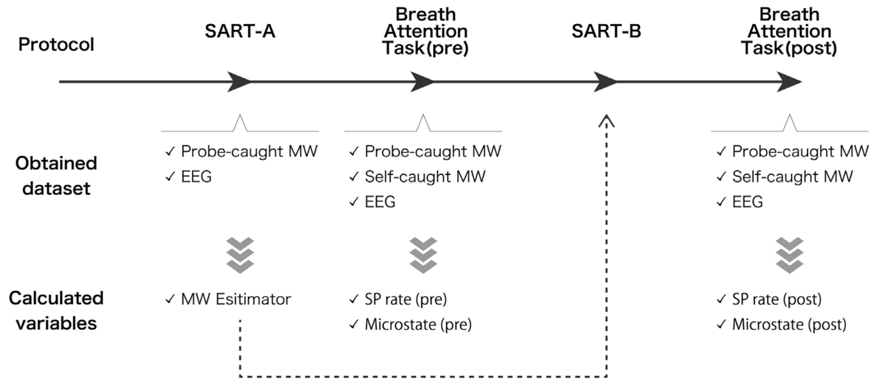

Fig. 1. Tasks and corresponding data and variables.

as an index of the meta-awareness of MW in previous research (Bastian et al., 2017; Sayette, Reichle, & Schooler, 2009; Sayette, Schooler, & Reichle, 2010; Schooler et al., 2011; Smallwood & Schooler, 2006). In this paper, we call this index the SP rate (Self-caught MW/Probe-caught MW rate) and hypothesize that the conditioning increases it.

As a secondary outcome, we compared the occurrence rate of the EEG microstate C between groups. It is known that the momentary scalp potential topographies are spatially patterned, and four common maps are clustered and seen in various previous studies; these maps are referred to as microstates and rapidly switch over at sub-second durations (Michel & Koenig, 2018). Research has investigated the relationship between these microstate maps and resting-state networks (Britz, Van De Ville, & Michel, 2010; Custo et al., 2017; Musso, Brinkmeyer, Mobascher, Warbrick, & Winterer, 2010; Pascual-Marqui et al., 2014; Yuan, Zotev, Phillips, Drevets, & Bodurka, 2012), and both a source localization study (Custo et al., 2017) and an EEG/functional magnetic resonance imaging (fMRI) simultaneous recording study (Britz et al., 2010) indicated that one microstate, often referred to as microstate map C, is presented by salience network activation. The salience network, which is anchored by the dorsal anterior cingulate and insular cortex (Seeley et al., 2007), is known to detect important environmental stimuli and switch our brain between the default mode network, which is the neural underpinning of MW, and the task-positive network (Menon & Uddin, 2010). Hasenkamp and Barsalou (2012) showed that the salience network was activated when participants noticed their MW, and indicated that it also detected a mismatch between attentional goal and current state (i.e., MW). Therefore, we consider that the occurrence of microstate C, representing salience network activation, is the most feasible of neuronal indices. However, its validity was not directly investigated and we treated it as just a secondary outcome, supplementarily supporting the result of the behavioral index.

2.3. Tasks

We prepared three tasks with Psychopy (Peirce et al., 2019): (1) The Sustained Attention Response Task (SART)-A for the machine-learning model fittings for MW, (2) the SART-B for the formation of classical conditioning, and (3) the breath attention task to assess meta-awareness ability. The three tasks and dataset obtained in each of them are shown in Fig. 1.

2.3.1. SART-A

SART-A is a modified version of the SART (Robertson, Manly, Andrade, Baddeley, & Yiend, 1997) to be applied to EEG recording and machine-learning analysis in order to estimate MW intensity. In the task, participants saw numerical digits (0, 1, 2, …, 9) presented one by one on the monitor and responded to them as quickly as possible by button press; however, if "3" was presented, they tried to hold off on pressing. Sometimes, a probe asking about the intensity of MW was presented and participants answered it.

SART-A comprised 150 blocks. Each block contained several trials, each involving one digit (except for the presentation of "3") and the participant's corresponding response. At the end of each block, either "3" or a probe asking about their intensity of MW was presented. Thus, the rate of digit "3" was 1.64% of all presented digits. Though participants performed all blocks successively, they could take a rest any time; if they stopped the task in the middle of the block, they resumed it from the start. The number of trials in each block (mean = 13.5, min = 9, max = 17), the order of digits, and probe presenting timings were decided pseudo-randomly. The digits were presented for 0.25 s, with a 0.9 s interval (Cheyne, Carriere, & Smilek, 2006; Gramfort et al., 2013). The mean interval between probes was 18.81 s.

The probe contains a question in Japanese, "Just now, how intensely focused is your mind on the task?" (Weinstein, De Lima, & van der Zee, 2018), with a visual analog scale labeled from "Intensely on task" to "Not on task at all". The answers on the scale were converted to scores from 1 to 100 points; we acquired 120 answers from each participant. Scientific operational definitions of MW are diverse, and a comprehensive approach is needed that evaluates them all, given that each definition has important characteristics for understanding the nature of MW (Seli et al., 2018). This study handles MW through the approach of MBI or mindfulness meditation, in which any task-unfocused state is treated as MW; that is, we adopt the broadest reasonable definition, conceptualizing MW as the state in which attention is not directed to the current task, regardless of task relativeness, stimulus-dependency, or guidedness of thought.

We recorded EEG during the task and extracted 1-s epochs just before probe presentation, acquiring 120 EEG epochs, one paired with each answer, reflecting the intensity of MW (see "Electroencephalogram" for details).

2.3.2. SART-B

SART-B is a modified version of the SART to be applied in classical conditioning between the perception and the suspension of MW. Though this task is basically the same as the SART-A, it includes 785 trials without probes and 1.75 s intervals; in addition, participants complete the task without a rest.

During the task, participants' EEG was transferred via the Lab Streaming Layer software and analyzed online, and the occurrence of MW was estimated once per trial (2 s; see "Fitting the machine-learning decoder" for details). In the 2-s trial, we used only the former 1 s, and the program was completed to estimate

MW and the present tone within the latter 1 s. The online EEG analysis was the same as that during the SART-A. When MW was detected, a 2000 Hz neutral tone was presented. However, if the participant was assigned to the RS group, the results of each estimation were abandoned and tones were presented at random times: the randomized values were chosen from the normal distribution, and if the value exceeded the threshold set for each participant (see ''Fitting the machine-learning decoder'' for details), tones were presented. We ensured that no significant differences were seen in the number of tones between groups ($t = -1.640$, $p = 0.110$). In both groups, once a tone sounded, its presentation was suppressed for 20 s. Until the debriefing at the end of the experiment, participants in both groups were instructed that tones were meaningless and to ignore them. Tone volume was modulated so as not to be aversive to each participant before the task started.

2.3.3. Breath attention task

The aim of the breath attention task was to evaluate MW meta-awareness ability. We instructed participants to focus on the abdominal sensation accompanied by their natural breathing and, when they noticed that they were absorbed in MW, to press the button and shift their attention back to their breath. A 500 Hz beep sound was presented as a probe asking them about their MW every 60 s approximately (pseudo-randomly jittered), and they pressed the button if they realized they were in MW due to the probe. The task continued for 904 s, and probes were presented 15 times.

The ratio of the number of occurrences of MW participants who noticed themselves to the number caught by probes is used as a behavioral index of the meta-awareness of MW (Bastian et al., 2017; Sayette et al., 2009, 2010; Schooler et al., 2011; Smallwood & Schooler, 2006); in this paper, we call it the SP rate (self-caught MW/probe-caught MW rate). To calculate the SP rate, we counted the number of button presses 0.2–4.0 s after the probe sound. We treated this count as the number of probe-caught MWs and presses at other times as self-caught MWs.

2.4. Procedure

Experiments were performed over 2 days. On the first day, we obtained informed consent from the participants; however, at this time, we withheld the true purpose of the study from them, informing them that it was a study investigating EEG patterns representing MW. This measure was considered because by informing them that tones (US) meant detected MW, the tones could function as punishers, and operant conditioning would be formed (instead of classical conditioning). Next, we introduced participants to the SART-A and the definition of MW. After a short practice session, participants performed the SART-A. Between the first and second day, we fitted a machine-learning-based decoder estimating the intensity of MW from EEG data (see ''Fitting the machine-learning decoder''). On the second day, participants were introduced to the SART-B and a breath attention task and practiced the breath attention task. Then, participants performed the breath attention task, took a short rest, completed the SART-B, and immediately performed the breath attention task again. After the participants performed all the tasks, we had time for debriefing, in which we explained to participants the true aim of the study and the reason why we concealed it until then.

2.5. Data loss and rejection

We excluded 14 participants' behavioral data, for the following reasons. Four were removed because small number of MWs (less than three) were detected during the SART-B. In the breath attention task at pre-conditioning, one reported no self-caught MWs, and three presented no probe-caught MWs. Further, in the task at post-conditioning, three reacted to all probes and one's probe-caught MWs was zero. One of 39 participants whose number of self-caught MWs was very large (>4 SD) and one whose SP rate was extremely high (>6 SD) were excluded as outliers. Moreover, EEG data from five participants during the breath attention task were lost due to technical errors. Thus, ultimately, we analyzed neural data for 32 participants and behavioral data for 37 participants.

2.6. Electroencephalogram

We used the Quick-30 (Cognionics Inc.) headset for EEG recording with 29 electrodes and an electrooculography (EOG) electrode placed under the right eye. We recorded EEG with a 500 Hz sampling rate during the tasks. We used the MNE-Python package for EEG analyses; the analysis details are found in the MNE Documentation (Gramfort et al., 2013), except for the microstate analysis following the Microstate EEGlab toolbox (Poulsen, Pedroni, Langer, & Hansen, 2018).

Regarding the EEG data during the SART-A and -B, we rejected data from Fp1 and Fp2 electrodes because of high contamination of the eye-blink artifact. We extracted the 1-s epochs just before presenting each probe (SART-A) or one 1-s epoch after the presentation of the number stimulus (SART-B). On each epoch, we applied a band-pass filter (5.0 Hz-47.0 Hz). Then, we removed the eye-blink artifact from the EEG epochs based on the fast independent component analysis (ICA; Hyvarinen, 1999): We decomposed each epoch into 12 components and zeroed out the one correlating highest to the EOG channel as the eye-blink-driven component. The number of components (i.e., 12) was decided by considering the calculation time on online analysis in the SART-B. We performed a fast Fourier transformation (FFT) on each epoch and channel and calculated band power in theta (7.0 Hz–8.0 Hz), alpha 1 (9.0 Hz–10.0 Hz), alpha 2 (11.0 Hz–12.0 Hz), beta 1 (13.0 Hz–18.0 Hz), beta 2 (19.0 Hz–21.0 Hz), beta 3 (22.0 Hz–30.0 Hz), and gamma (35.0 Hz–44.0 Hz).

Regarding the EEG data during the breath attention task, we applied a band-pass filter (2.0 Hz–49.0 Hz) and excluded bad segments and channels manually. Bad channels were interpolated. We set the threshold of the number of bad channels as 20% of electrodes (i.e., six electrodes) and confirmed that no EEG data exceeded this threshold. Then, we performed fast ICA and decomposed data into 29 components, manually rejecting bad components and excluding bad segments again. We performed microstate analysis following Poulsen et al. (2018). First, we applied a band-pass filter (2.0 Hz–20 Hz) and average reference. Then, we randomly selected 1000 sample points from where global field power indicated peaks (but less than 1 SD) of each recording of pre- and post-conditioning. The global field power is the SD of each channel's signals at one sample point and is known to be an index of the signal–noise ratio. We classified these sample points into four clusters (the microstate template maps) by modified k-means with 10-times restart with different centroid seeds and 1e-06 threshold of convergence. In this way, we acquired four microstate template maps as shown in Fig. 3D; all sample points (except for bad segments) of all recordings were classified into one of these maps. The explanation rate of these maps for all EEG data variance (global variance explained: GEV) was 60.8%. In the EEG microstate analysis, though the obtained GEV of the four maps was not very high in previous microstate research, it was still validated that our scores were similar or better than those in previous studies (Corradini & Persinger, 2014; Custo et al., 2017) and that the maps were consistent with those in previous literature (Michel & Koenig, 2018).

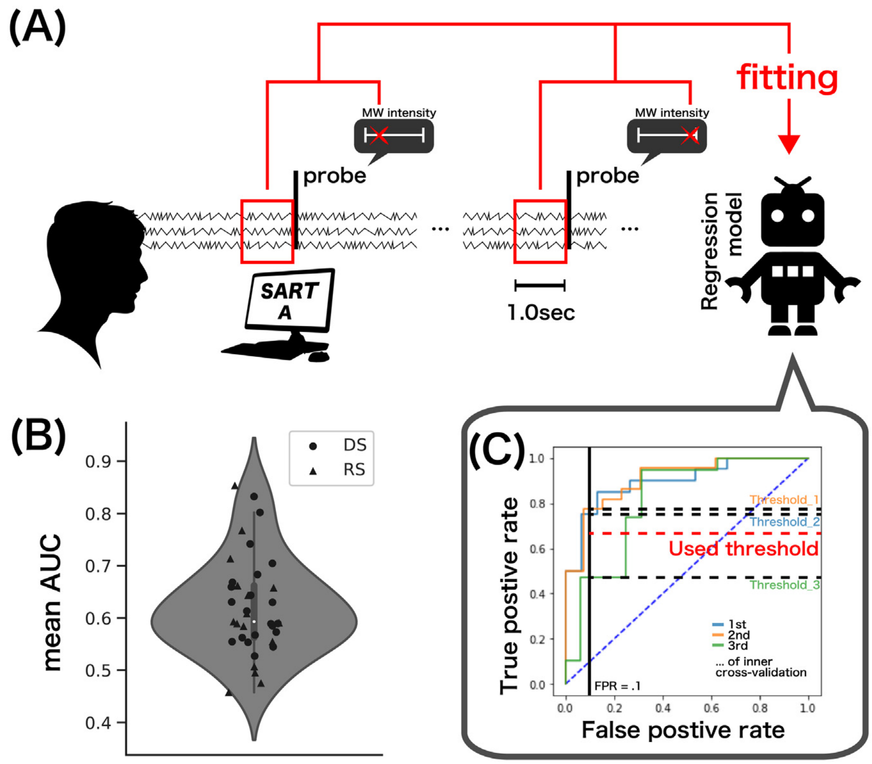

Fig. 2. The detection of MW from EEG. (A): The data collection procedure for fitting machine-learning models. For each participant, we fitted a machine-learning-based decoder estimating the report of MW from EEG and self-report data during the SART-A. (B): Thresholding based on the ROC curves. To classify dichotomic converted MW intensity with the regression model, we drew receiver operating characteristic curves for every three outer cross-validations and found the thresholds for a maximal true positive rate, keeping the false positive rate under 10%. We adopted the mean value of three thresholds. (C): The distribution of the mean area under the curve. We calculated and plotted the mean area under the curve of three times outer cross-validation. DS: Detected Sound group; RS: Randomized Sound group; AUC: area under the curve. The triangular points denote RS, and the round ones denote DS.

A smoothing method based on small maps rejection (Poulsen et al., 2018) was applied, and each microstate was constrained to continue for at least 10 ms (50 sample points). Finally, the number of occurrences of the microstate map C (the salience network-related state) per second was counted in each recording.

2.7. Fitting the machine-learning decoder

We fitted a machine-learning-based decoder estimating the intensity of MW from EEG and self-report data during the SART-A (Fig. 2A). The models were fitted for every participant, and all fitting protocols, described below in this section, were also conducted for each participant. For the fitting, we used EEG band power values as predictors (27 electrodes $\times$ 7 bands $=$ 189 predictors; see previous section) and 120 MW intensity reports as target values. Though the final goal of the decoder was a binary prediction of the occurrence of MW, we first made regression models because the target values were continuous data. After fitting a regression model, we converted continuous target values into dichotomic values by their average and set a threshold (detailed below) so that the regression model could perform binary classification (Fig. 2B).

We constructed a data pre-processing and decoder-fitting pipeline. First, the pipeline normalized the training dataset and equalized the mean and variation of each predictor. Next, outlier samples were detected based on the local outlier factor (LOF; Breunig, Kriegel, Ng, & Sander, 2000) and replaced with the mean values of the training dataset. The LOF is an index of the outlier calculated by the local density of the data sample: A sample whose position in variable space is distant from neighbors has a high LOF and is detected as an outlier. Then, features relating to target values (i.e., MW reports) were selected according to a percentile of the highest single regression and entered into the support vector machine regression (linear kernel). The number of features to be selected, LOF threshold, and hyper-parameters of support vector machine regression were decided by grid search, in which numerous tentative models were fitted with all combinations of parameter candidates, and the parameter set producing the best model was employed.

We validated each decoder's accuracy with 3 $\times$ 10 nested cross-validation: We split data into three and held-out one of them as test data, and with the remaining data, we performed fivefold cross-validation (inner cross-validation) to explore valid parameters by grid search; then, we set the 2nd and 3rd split data as test data and repeated the same procedure. Note that for test data in cross-validation, normalization was performed with SD and mean value of training data, and the features selected in training data were used. For every three procedures, we evaluated the prediction performance with test data (threefold outer cross-validation). For each outer cross-validation, we divided the target values by the average and converted them into dichotomic data. Then, we drew a receiver operating characteristic curve, calculated the area under the curve (AUC) as an index of the prediction accuracy of the decoder, and found a threshold to maximize the true positive rate while keeping a false positive rate under 10% (Fig. 2B). Finally, we fitted a model with all the data and set the threshold for each participant as the mean of the thresholds calculated by three outer cross-validations. We applied the fitted decoder, including SD and mean value for normalization and selected features, to EEG data during the SART-B, processed as the SART-A EEG data. To contribute to future studies, we calculated the correlations between AUC and all other indices of participants; the results are presented in Table A.1. We used the scikit-learn library for machine-learning preprocessing and fitting (Pedregosa et al., 2011).

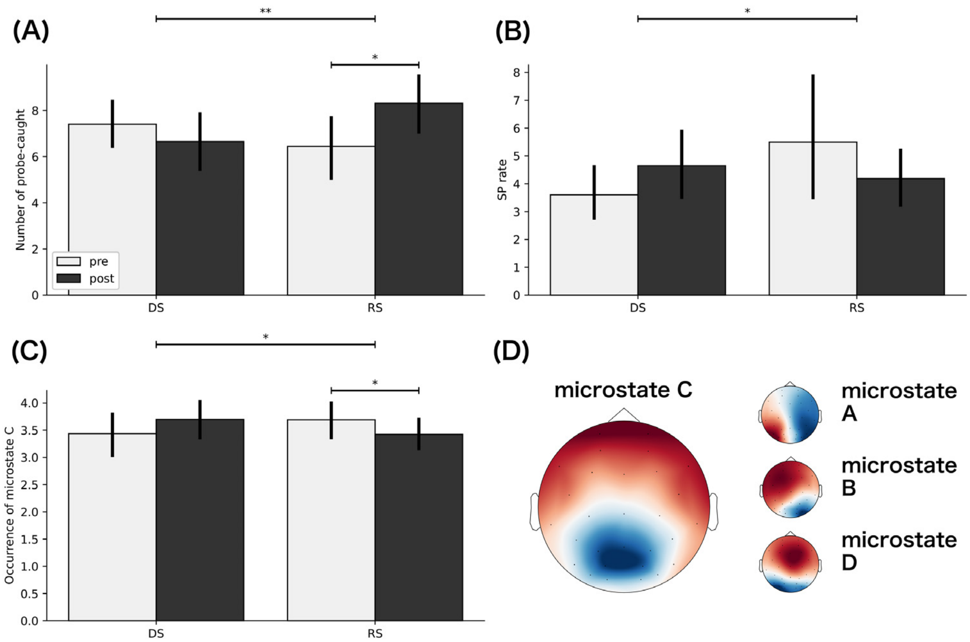

Fig. 3. The pre- and post-conditioning scores. We applied ANOVAs to the pre- and post-conditioning scores for the number of probe-caught MWs (A), SP rate (B), and the occurrence of EEG microstate C (C). White bars mean pre-conditioning scores, and black ones mean post-conditioning. The top vertical lines mean significant interactions of timing × group. The second lines from the top denote significant differences between pre- and post-conditioning scores in the post-hoc analysis. *: p < .05. **: p < .01. The error bars denote SD. (D): Four template maps of the microstate. These four template microstate maps were extracted from the timing-and-group-collapsing of all EEG data during the breath attention task. The global variance explained (GEV) was 60.8%. We used the occurrence frequency of map C (the largely displayed one) for analysis.

2.8. Statistics

We applied a mixed-model two-way analysis of variance (ANOVA) with the factors of group (DS/RS) and time (pre/post) for the following variables: number of probe-caught MWs, SP rate, and map C occurrences in EEG microstate analysis. As post-hoc analyses, we compared the pre- and post- values of these factors in each group using paired t-tests when significant interactions were seen. To check group differences in participants' age and the number of tones in the SART-B, we performed two-sample t-tests between DS and RS groups. As additional analyses, the same ANOVAs were conducted on the occurrence of microstates A, B, and D, and the mean duration and the coverage (the temporal percentage for which a given microstate is dominant) of microstate C (Michel & Koenig, 2018). The results of these additional tests are reported in the appendices (Table A.2, A.3, and Figure A.1). Further, to support that the MWs were suspended after tone presentation in the SART-B, we analyzed data with a multilevel model. In the model, we assumed a random effect intercept and that the estimated MW intensities in three trials before/after tone presentation (level 1) were nested within participants (level 2).

These statistical analyses were performed using the Pingouin package (Vallat, 2018) and the Statsmodel package (Seabold & Perktold, 2010) in Python.

3. Results

We confirmed that there were no significant differences in age between the DS and RS groups ($t = -0.670$, $p = .508$). The mean AUCs of fitted models calculated by three outer cross-validations are indicated in Fig. 2C. The median of these values was .601 (.458–.854). The mean occurrence rate of the target value (i.e., dichotomized MW) in each participant was 35.89% (21.71%–46.05%). From our timing-and-group-collapsing of all EEG data during the breath attention task, four template microstate maps were extracted, as indicated in Fig. 3D. The explanation rate of these maps for all EEG data variance (global variance explained: GEV) was 60.8%. During the SART-B, a tone was presented when MW was detected from the real-time EEG data in the DS group, while it was presented at random times in the RS group. We ensured that no significant differences were seen in the number of tones between groups ($t = -1.371$, $p = .182$). The average number of tones was 35.750 ± 17.727 (RS group: 40.375 ± 20.370; DS group: 32.050 ± 14.795) Further, the multilevel analysis indicated that the estimated MW intensities in the SART-B significantly decreased after tone presentations ($\beta = -0.043$, $Z_{Wald} = 2.324$, $p = 0.020$).

The mixed-model two-way ANOVA with the factors of group (DS/RS) and timing (pre/post) found a significant group × timing interaction on the number of probe-caught MWs ($F_{1,34} = 9.402$, $p = .004$, $p\eta^2 = .217$; Fig. 3A), SP rate ($F_{1,34} = 4.546$, $p = .040$, $p\eta^2 = 0.118$; Fig. 3B), and the occurrence of microstate map C ($F_{1,29} = 5.198$, $p = .030$, $p\eta^2 = 0.152$; Fig. 3C). The post-hoc analysis revealed the simple main effect of timing on the RS group for the number of occurrences of probe-caught MWs ($t = 2.654$, $p = .018$, $g_{Hedge} = 0.673$; Fig. 3A) and map C ($t = -2.149$, $p = .0496$, $g_{Hedge} = -0.445$; Fig. 3C). However, the simple main effect on the SP rate was not significant (on the DS: $t = 1.713$, $p = .103$, $g_{Hedge} = 0.408$; on the RS: $t = -1.347$, $p = .198$, $g_{Hedge} = -0.353$; Fig. 3B). No simple main effects of timing on the DS group were significant (for number of probe-caught MWs: $t = -1.449$, $p = .164$, $g_{Hedge} = -0.277$; for microstate C: $t = 1.362$, $p = .193$, $g_{Hedge} = 0.344$).

4. Discussion

The significant group × timing interaction on the SP rate, the behavioral (Bastian et al., 2017; Sayette et al., 2009, 2010; Schooler et al., 2011; Smallwood & Schooler, 2006) index of meta-awareness of MW, supported our hypothesis of conditioning effects on the meta-awareness of MW. In addition, a significant interaction on the occurrence of the microstate C, the feasible neural index of meta-awareness (Britz et al., 2010; Custo et al., 2017; Hasenkamp & Barsalou, 2012), was also observed and supported the behavioral result, though it is not a sufficiently validated index. The post-hoc analysis revealed that the occurrence of the microstate map C significantly decreased in the second task in the group without conditioning. Meanwhile, the simple main effect for the SP rate was not significant. The frequency of absorption in MW is well known to increase with task repetition (Esterman, Noonan, Rosenberg, & DeGutis, 2013; Krimsky, Forster, Llabre, & Jha, 2017; Smallwood, Obonsawin, & Heim, 2003), and we believe that meta-awareness is also reduced by the boredom associated with repeated tasks. The post-hoc t-test results are consistent with this notion, and we interpret interactions on SP rate and map C occurrence as showing a potential increment of meta-awareness due to conditioning. However, the decline due to task repetition offset it.

Interestingly, the same interaction pattern and simple main effect of timing on the RS group was seen in the number of probe-caught MWs, a popular index of the propensity to become absorbed in MW during a task (Weinstein et al., 2018). This could imply that the conditioning reduces probe-caught MW, although this was not expressed in the hypothesis. Considering that the volumes of presented tones were tuned so as not to be aversive for participants and that they did not know that the tone reflected their MW, the conditioning did not seem to suppress the occurrence of MW. Therefore, we contend that this decline in the DS group was also driven by the enhancement of meta-awareness of MW. A previous researcher indicated the possibility that the meta-awareness of MW decreases the number of probe-caught MWs because it can help participants reduce the amount of time they spend in MW (Smallwood, 2013). However, the relationship between meta-awareness of and tendency toward MW is unclear in previous research and remains unclear in this study; thus, from the current study's results, we could not determine the reason behind the increase in the number of probe-caught MWs. The interpretation that enhanced meta-awareness decreased the number of probe-caught MWs raises a concern about the validity of the SP rate as a measure, which is based on the assumption that the number of self-caught MWs reflects both propensity to and meta-awareness of MW while the number of probe-caught MWs reflects only propensity; if so, the ratio between self-caught and probe-caught MW can be an index of the meta-awareness of MW (Schooler et al., 2011; Smallwood & Schooler, 2006). Our results may contradict part of this assumption; however, in that case, we argue for the effect of the conditioning based on the decrease in probe-caught MW, instead of the interaction on the SP rate.

One of the novel points of the current study is that our neurofeedback was based not on operant conditioning but on classical conditioning. Considering that our proposed conditioning feedback participants' neural information, we should consider it a form of neurofeedback. However, in some ways, our method is different from typical neurofeedback protocols. The most traditional and popular framework interprets neurofeedback as a form of operant conditioning (Enriquez-Geppert, Huster, & Herrmann, 2017; Kamiya, 2011), explaining that the frequency of a given behavior increases or decreases due to consequent reward or punishment, whereas in contrast, in the conditioning conducted here, participants did not receive any reinforcer or punisher. Because we adjusted the volume of the tones so as not to annoy participants and to avoid letting participants interpret the tones as criticism of their MW (i.e., punisher), we informed them that the tones were random and meaningless. We did not ensure whether participants realized that tones were triggered by their MW during the task. However, we consider that just suspecting the hidden meaning of tones in the middle of the task would not produce punishers that could establish the operant conditioning. Although operant conditioning would have occurred if participants realized the true purpose of our study and were confident that tones would mean their MW before or at the outset of the task, it is quite unlikely. While the establishment of operant conditioning requires some reinforcer or punisher, these are not necessary for the establishment of classical conditioning (Damianopoulos, 1982). Hence, our conditioning cannot be considered to be operant conditioning instead of classical conditioning. Though researchers have indicated that various cognitive processes, including classical conditioning, contribute to the success and transfer of conventional neurofeedback (Sitaram et al., 2017; Strehl, 2014; Wood, Kober, Witte, & Neuper, 2014), no previous research has performed neurofeedback omitting operant conditioning from its core mechanism and using classical conditioning instead. Since this conditioning is not operant-based but classical, it has the merit that its effect will depend less on participants' motivation.

We used online EEG data and a machine-learning technique to detect the occurrence of MW, but the MW monitoring method is not essential for the conditioning. The development of MW monitoring technology can be introduced to the conditioning. Some physiological signals, such as oculometrics (Grandchamp, Braboszcz, & Delorme, 2014; Mittner et al., 2014; Unsworth & Robison, 2016), skin conductance response and skin temperature (Blanchard, Bixler, Joyce, & D'Mello, 2014), and heart rate (Pham & Wang, 2015), have been shown to relate to MW. Further, some studies have tracked MW via reaction performance to the task (Bastian & Sackur, 2013; Esterman et al., 2013). The estimator was fitted based on self-ratings of MW; thus, the tones were presented at different levels of MW between participants. It is possible that some might have received the tones only when they were intensely absorbed in MW while others heard the tones when they experienced moderate MW. This might vary the neurofeedback quality in the DS group, though the total effect was significant.

This research has some limitations. First, we excluded participants who showed the maximum number of probe-caught MWs or who showed no probe-caught MW or self-caught MW. Hence, we did not reveal an effect of conditioning on people whose MW-related characteristics, such as MW tendency or meta-awareness ability, were extremely high or low.

Second, we evaluated the effect just after the conditioning, and did not investigate how long the effect continued. We think the effect of the current conditioning setting (20 min, once) would likely not continue a long time and would not generalize to daily life, because participants appear to have let their minds wander without US presentation; the conditioning they received would then become extinct rapidly. Although the temporary enhancement we have gained would be sufficient for the purposes of a longitudinal study of meta-awareness, a future study investigating whether repeated conditioning sustains this effect and whether that effect can be seen in participants' daily life is needed. It can be hypothesized that methods which increase meta-awareness in daily life would be good interventions to ameliorate task performance and mood and mitigate mental health concerns such as depression, given the suggested roles of MW and its meta-awareness (Bozhilova et al., 2018; Burg & Michalak, 2011; Deng & Li, 2012; Franklin et al., 2017; Keith, Blackwood, Mathew, & Lecci, 2017; Killingsworth & Gilbert, 2010; Marchetti et al., 2012; McVay et al., 2009; Ottaviani & Couyoumdjian, 2013; Perkins et al., 2015; Randall et al., 2014; Robison, Gath, & Unsworth, 2017; Seli, Risko, Purdon and Smilek, 2017; Seli, Risko, & Smilek, 2016; Shin et al., 2015; Smallwood, McSpadden, Luus et al., 2008; Smallwood, O'Connor, Sudbery, & Obonsawin, 2007; Stawarczyk et al., 2012; Williams et al., 2018; Zedelius & Schooler, 2016). Such methods may help to indicate the relationship between meta-awareness and creativity. It seems quite reasonable to hypothesize that the meta-awareness of MW encourages conscious access to each idea manifesting during an MW and thereby facilitates the expansion of creativity. We cannot consciously know what we thought about without noticing that the mind was wandering. However, some previous studies failed to prove the same (see Teng & Lien, 2022). All these studies were cross-sectional designs and intervention research with our method may lead the other result. This also may contribute to the study of MBI. The mechanism by which MBI reduces depression (Khoury, Knäuper, Schlosser, Carrière, & Chiesa, 2017; Khoury et al., 2013) and enhances creativity (Lebuda, Zabelina, & Karwowski, 2016) is unclear, and researchers have found that various factors complexly interact to bring about these outcomes (Shapiro, Carlson, Astin, & Freedman, 2006; Tang et al., 2015). Part of those effects might be understood as enhancing meta-awareness by repeatedly practicing being aware of and observing one's MW (Konjedi & Maleeh, 2017; Teasdale et al., 2000; Vago, 2014) and thereby controlling the function of MW. Comparing the benefits from pure meta-awareness increment and MBI would elucidate to what degree meta-awareness explains the effect of mindfulness. Even if meta-awareness enhancement does not affect quality of life, it might perform the same function as basic training in mindfulness meditation and promote MBI.

Third, the required precision of the MW decoder for neurofeedback has not been studied. The reported AUC may not reflect the true accuracy of estimators because predictions were performed on a different day from when the models were fitted, and the dataset for machine-learning fitting was not balanced (35.89%), which may have skewed the AUC. The precision of our estimators was not very high and may be less than reported. This may indicate that the proposed neurofeedback method can accept not only a very accurate estimator, but a range of newly developed prediction models, such as those in future work. However, we did not investigate the lowest precision required for neurofeedback. Moreover, the possibility that the more accurate decoder produces a better effect was not studied. The more advanced machine-learning method, including a deep convolutional neural network (Hosseini & Guo, 2019) and random forest (Chen et al., 2022) or combination with fMRI data (Groot et al., 2021) might yield better predictions.

Finally, while the current study proposed classical conditioning using neurofeedback and posited the perception of MW as its CS, we did not clarify the details of this perception, such as its modality. We consider CS to be an interoceptive sensation accompanied by the occurrence of MW. Previous research has shown that MW induces several interoceptive responses indexed by pupil dilation, which is closely associated with the locus coeruleus-norepinephrine system (Franklin et al., 2017; Unsworth & Robison, 2016) and skin conductance and temperature (Blanchard et al., 2014). Also, though it has not been investigated yet, MW may plausibly cause some changes in posture and muscular contraction/relaxation. These interoceptive responses to MW can be unconsciously or consciously perceived and serve as conditioned stimuli, as reflected in recent research demonstrating that classical conditioning can be established through subliminal CS (Jensen, Kirsch, Odmalm, Kaptchuk, & Ingvar, 2015). Further research that clarifies the modality of perception in CS can not only support the current results but also might hint at why mindfulness meditation, used here as training for the meta-awareness of MW, has traditionally emphasized attention toward the body.

4.1. Conclusion

We proposed a Pavlovian-based EEG neurofeedback approach and developed a method to heighten the meta-awareness of MW. We demonstrated that one short session of the conditioning, designed to let participants momentarily suspend MW when they start it, enhanced the meta-awareness of MW. Whereas previous research using neurofeedback implemented neurofeedback training and tried to regulate participants' MW tendencies (Gonçalves, Carvalho, Mendes, Leite, & Boggio, 2018), the current study applies neurofeedback training targeting the meta-awareness of MW. This study could thus support future interventions in and further research of the meta-awareness of MW.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.neunet.2022.11.024.

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