**No effect of focused attention and open monitoring meditation on
EEG auditory mismatch negativity in expert and novice
practitioners**

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Abstract

The auditory mismatch negativity (MMN) is a well characterized event-related potential component which has gained recent attention in theoretical models describing the impact of various styles of mindfulness meditation on attentional processes and perceptual inference. Previous findings highlighted a distinct modulation of the MMN amplitude by different meditation practices and degrees of expertise. In the present study, we attempted to replicate results from the recent literature with a data sample that allowed for increased statistical power compared to previous experiments. Relying on traditional frequentist analysis, we found no effect of focused attention and open monitoring meditation on the auditory MMN amplitude compared to a control condition (silent movie) in expert or novice practitioners (all $p > .17$), providing a non-replication of our previous work (Fucci et al., 2018). Using a Bayesian approach, we found strong evidence against an interaction effect on the MMN amplitude between expertise groups and meditation practices ($BF_{01} = 11.0$), strong evidence against effects of either meditation practices compared to the control condition (BF_{01} between 11.9 and 16.1) and moderate evidence against an effect of expertise during meditation (BF_{01} between 5.3 and 7.9). On the other hand, we replicated previous evidence of increased alpha oscillatory power during meditation practices compared to a control state ($p < .001$). We discuss our null findings in relation to factors that could undermine the replicability of previous research on this subject, namely low statistical power, use of flexible analysis methods and a possible publication bias leading to a misrepresentation of the available evidence.

Keywords: Mindfulness, EEG, MMN, Replication, Alpha power, Meditation

1. Introduction

The understanding of the neurocognitive processes involved in mindfulness meditation has increased considerably over the last few years. Neuroimaging studies have identified neuroanatomical and neurophysiological markers of attention and emotion regulation as correlates of state and trait effects in different meditation styles and groups of practitioners (see Deolindo et al., 2020; Fox et al., 2016; Lutz et al., 2008; Tang et al., 2015 for extensive and critical reviews). The investigation of biological markers of mindfulness meditation plays a major role in apprehending the mechanisms underlying mindfulness-based interventions in clinical and other applied settings. Neurophysiological data is also essential to the operationalization of meditation practices into psycho-cognitive models and to support a dialogue between contemplative and scientific inquiry on fundamental research questions (e.g. Dahl et al., 2015; Lutz et al., 2015). Based on these premises, assessing the validity and replicability of the evidence for the modulation of relevant neural markers by meditation states and expertise is a necessary and critical task. In this article, we report the outcome of a replication study assessing the reliability of the auditory mismatch negativity (MMN) as an electrophysiological marker of attentive and predictive processes influenced by different styles and degrees of experience in mindfulness meditation.

The MMN is a stimulus-evoked neurophysiological response elicited by a sudden change in a stream of repeating sensory stimuli. It can be recorded using electroencephalography (EEG) through experimental paradigms, named “oddball task”, consisting of sequences of repeating stimuli (standard) perturbed by infrequent stimuli (deviant) that can differ in terms of frequency, intensity, duration and other features (Näätänen et al., 2007). In general, the MMN is obtained by subtracting the average response to the last standard stimulus before a deviant from the response to the deviant stimulus. In its auditory form, this event-related potential (ERP) component peaks between 100 and 200 ms after stimulus onset (Sams et al., 1985) and

is distributed over frontocentral scalp areas, prominently in frontal regions. The auditory MMN has been widely studied in the field of neurophysiology for more than three decades, also due to the ease in recording it using non-invasive techniques in different populations and developmental stages. As a neural marker of sensory and attentive processing, it has been informing neuroscientific models of cognition (Sussman & Shafer, 2014; Näätänen et al., 2007) and has been used as an index of cognitive dysfunction in psychiatric and neurological patients (Näätänen et al., 2014). More recently, its underlying mechanisms and its functional significance have been reframed in the context of the overarching psychobiological theory of predictive coding (Friston & Kiebel, 2009). Within the predictive coding framework, the MMN is described as a marker of precision-weighted prediction error signals involved in implicit perceptual learning processes (Garrido et al., 2009). This account of the MMN has been supported by neuroanatomical and neurocomputational models describing bottom-up and top-down neural pathways conveying predictions and prediction-error signals within a hierarchical structure that encompasses the auditory cortex as well as prefrontal brain regions (Garrido et al., 2008; Wacongne et al., 2012). This has also led to a revaluation of the mechanisms underlying MMN modulation in psychiatric conditions such as schizophrenia (Rentzsch et al., 2015).

Up to date, few studies reported an effect of meditation on the amplitude of the auditory MMN. Increased MMN was observed during forms of focused attention (FA; Lutz et al., 2007) meditation as a state effect in both expert (Srinivasan & Baijal, 2007) and novice practitioners (Braboszcz & Delorme, 2011) and as a trait effect in expert practitioners compared to novices (Srinivasan and Baijal 2007, Biedermann et al., 2016). In a recent study, Fucci et al., (2018) reported an interaction between meditation experience and styles of practice, showing a larger MMN amplitude in expert practitioners during FA compared to a control condition and novice practitioners. However, no effect on the MMN amplitude was observed in the same expert

practitioners during a form of advanced, objectless practice considered to entail a state of nondual awareness (open presence, OP; Lutz et al., 2007).

The results from these studies have been quoted as supporting evidence of increased attentional and perceptual performance by meditation practice (e.g. Josefsson & Broberg, 2011; Ramsburg & Youmans, 2014; Vago & Silbersweig, 2012) and in the context of reviewing how the MMN can be influenced by specific states of consciousness (Näätänen et al., 2012). More recently, the results from Fucci et al. (2018) have been quoted in theoretical works proposing a predictive coding account of meditation practices (Laukkonen & Slagter, 2021; Lutz et al., 2019; Pagnoni & Guareschi, 2017). Within this framework, larger MMN amplitude during FA would reflect the monitoring of task-unrelated events enhancing the brain responses to deviations in the auditory environment. The state of OP, in turn, would entail a reduction in the formation of perceptual predictions and, as a result, a decreased MMN amplitude even when attention is not diverted from the auditory stream.

Previous studies, however, were conducted on small samples of participants, an issue that has a detrimental effect on reproducibility (Button et al., 2013) and that has been argued to represent a recurrent limitation in meditation research (Davidson & Kaszniak, 2015). Moreover, as it is the case for a large part of the literature in neuroscience and psychology, experiments implementing similar paradigms may have not analyzed the MMN amplitude or may have not reported null findings (Ferguson & Brannick, 2012). Finally, previous evidence was obtained using traditional frequentist approaches to statistical analysis, which may cause an overestimation of effect sizes or even errors in effect direction when applied to underpowered studies (Gelman & Hill, 2006).

In the present work, we sought to address these limitations and replicate previous findings showing a differential modulation of the MMN amplitude by FA and OP meditations in experts compared to a control state and novice practitioners. We did so in the context of a passive

auditory oddball task similar to the one implemented in Fucci et al. (2018) and studying an adequately powered sample size of expert and novice meditation practitioners during FA and OP styles of meditation. As in the previous experiment, we expected to observe an interaction between groups and meditation states. Specifically, experts would show a larger MMN amplitude during FA compared to a control state and OP, as well as a larger MMN during FA compared to novices. We tested this hypothesis using both frequentist and Bayesian statistical approaches.

As part of our replication effort, we analyzed EEG oscillatory activity in the alpha (8-12 Hz) frequency band. We expected to observe, in line with Fucci et al. (2018), increased power over this frequency band during meditative states compared to a control condition in both expert and novice practitioners. Increased alpha power during meditation practice has been frequently reported (Ahani et al., 2014; Lagopoulos et al., 2009; Takahashi et al., 2005; Yu et al., 2011), but null or opposite results were also found (Amihai & Kozhevnikov, 2014; Braboszcz et al., 2017; Cahn et al., 2010, Kubota et al., 2001; see Cahn & Polich, 2006; Lee et al., 2018 and Lomas et al., 2015 for exhaustive reviews). In the same way, the presence of a trait effect of meditation experience on alpha power is reported inconsistently depending on meditation traditions and degrees of expertise (Cahn & Polich, 2006). For example, Fucci et al. (2018) did not observe any significant differences between long term meditators and novices. In the current report we explored the effect of meditation expertise on alpha oscillations in a larger sample of participants.

2. Methods and Materials

2.1 Subjects

Thirty expert meditation practitioners (52 ± 7.8 years old, 13 females, right-handed, 3 ± 2.62 years of higher education, all white Caucasians) and thirty-six control healthy participants (52 ± 7.6 years old, 17 females, right-handed, 3 ± 2.33 years of higher education, all white Caucasians) participated in the study. Control participants (hereafter referred to as “novices”) were recruited locally through flyers and posters in public places, mailing lists, social media and notifications to research participant databases. Novices underwent a weekend-long introduction to meditation and practiced at home before participating in the experiment (see section 2.2 for details). Expert practitioners (> 10.000 hours of practice and at least one 3-years intensive retreat) were recruited from multiple meditation centers, predominantly in France but also internationally, with the help of a long-term practitioner with extensive contacts within the Nyingma and Kagyü communities of Tibetan Buddhism. The present study was part of a larger research project that included several experimental sessions. A detailed description of the general inclusion and exclusion criteria for expert and novice practitioners is provided in a separate document (Abdoun et al., 2018; accessible online at osf.io/dbwch). For this specific study, relevant exclusion criteria were: use of psychoactive medications, history of neurological or psychiatric conditions, history of chronic pain or other conditions involving sensitization to pain, personal or family history of epilepsy, severe hearing loss. All participants provided proof of affiliation to social security, signed an informed consent before the beginning of the experiment, and were paid for their participation. Ethical approval was obtained from the appropriate regional ethics committee on Human Research (CPP Sud-Est IV, 2015-A01472-47).

2.2 Meditation practices and training

The distinction between focused attention (FA) and open monitoring (OM) styles of meditation has been extensively discussed in previous theoretical work (Lutz et al., 2008). In the present study, during the FA practice, participants were asked to focus on a fixation cross as the object of meditation, in line with our previous research (Fucci et al. 2018). The choice of this specific object was done to allow for an unbiased comparison with the control state, when subjects watched a silent documentary on the same screen. During the OM practice, a fixation cross was present on the screen and subjects were asked to keep their eyes open. Practicing meditation with eyes open is a common feature of the Nyingma and Kagyü schools, which all expert practitioners who participated in this research belonged to. It is also suggested in the training program undergone by control participants, which derives from the same traditions of Tibetan Buddhism. In the present study, keeping the eyes open helped avoiding the contamination of the EEG signal by alpha oscillatory activity.

It is important to notice that novice and expert practitioners differ in their style of practicing OM meditation. Specifically, the present group of expert meditators was intensively trained in practices aiming at recognizing and sustaining the “nature of the mind” (Tib. Wylie, *sems nyid* or *sems kyi rang bzhin*) or one's “fundamental awareness” (Tib. Wylie, *rig pa*). In their case, practicing meditation without object is related to maintaining a state previously referred to as open presence (OP) (e.g. Lutz et al., 2007). Within this state, an awareness of whatever emerges in experience continues without the effortful vigilance that characterizes OM styles of practice (see the notion of “reflexive awareness” in previous works, e.g., Coseru, 2015; Dunne, 2011). However, as we mentioned in previous research (Fucci et al., 2018), the state of OP is characterized by a high degree of variability between subjects and within a specific session. In the present study, experts were recruited based on their capacity to recognize and stabilize the state of OP (following teachers’ recommendations and peer validation facilitated by direct

contact with the communities of practice) and were instructed to engage with this specific practice. Novice practitioners were introduced to the practices of FA and OM meditations during a weekend-long training program and were asked to practice at home during the period preceding the experiment (see Abdoun et al., 2019 for a detailed account of subjects' degree of compliance to the home practice).

2.3 Task design and stimuli

The experiment consisted in a passive auditory oddball task (e.g. Näätänen et al., 2004). In this task, variable sequences of standard tones (880 Hz; 80ms duration; 10ms rise and fall) were followed by the presentation of a frequency deviant (988 Hz; 20% of all auditory stimuli). The stimuli were presented binaurally (fixed inter-stimulus interval = 500ms). To increase the number of observations per subject while keeping recording time reasonably short, the paradigm comprised two sessions. Each session included three experimental conditions (named "states" hereafter): focused attention meditation (FA), open presence (OP) meditation (or open monitoring [OM] meditation for novices) and a control state during which subjects were asked to watch a silent movie (extraits from the documentary "Baraka", 1992; <https://www.barakasamsara.com>) and ignore the auditory stimuli (VD). We informed the participants that this condition was a control state where the mind lets itself be absorbed by the content of the silent movie and is thought not to exhibit spontaneous meditative qualities. We used an active control state which entailed attending a visual object to minimize confounds when comparing it with the two meditation conditions (both involving a fixation cross). This was also in line with conditions commonly used in passive oddball paradigms where participants are instructed not to pay attention to the auditory stimuli. State order was randomized within each session. Each state-block (~6 minute long) started with a 2 minutes period with no auditory stimuli. During this time, subjects were asked to meditate or watch the

silent movie, depending on the state instructions. Subsequently, oddball sequences were embedded in alternating 30s periods (8 periods per block) in which participants were informed of the possibility of receiving an electric shock (threat periods, $n = 4$) or that no shocks would be delivered (safe periods, $n = 4$) [as in Cornwell et al., 2007]. Safe and threat periods consisted of the same number of stimuli ($n = 56$ deviants and $n = 224$ standards when combining the four periods of each state). For the aim of the present research, where we sought to replicate previous findings on the effect of meditation states and expertise on event-related potentials and brain oscillatory activity in an emotionally neutral condition, we conducted statistical analysis excluding threat periods. Results from the analysis of the effect of threat on event-related potentials in novice practitioners are reported in Fucci et al. (2019). At the end of each block, participants answered (on a 1 to 7 Likert-item) questions about their subjective experience during the task. The results of the analysis of self-reports will be described elsewhere.

2.4 EEG recordings

EEG was recorded with the ActiveTwo system (BioSemi, Amsterdam, Netherlands) and sampled at 512 Hz. The recording system consisted of 64 active electrodes positioned on a cap following the standard 10/20 coordinates. The horizontal and vertical EOG was measured by placing flat electrodes on the outer canthi and above and below the subject's left eye. Electrodes were kept within an offset of 50 mV (± 25 mV) using the Biosemi ActiView data acquisition system for measuring signal quality. Recordings were performed in a highly shielded Faraday chamber.

2.5 EEG Data preprocessing

EEGlab (Delorme & Makeig, 2004) and in-house Matlab scripts (version R2015a) were used for data pre-processing. Raw recordings were downsampled to 250Hz and re-referenced offline based on the electrodes placed on the mastoids (average activity of the two channels). Bad channels (affected by muscle-related activity over long periods of time) were identified by means of visual inspection and subsequently marked for being interpolated. We applied Independent Component Analysis (ICA) to the continuous data using the Runica algorithm (Makeig et al., 2002), distinctly for the two recording sessions. Data that underwent ICA were manually cleared of large movement-related artifacts following examination of the raw EEG (performed by the first author of the manuscript, who had previous experience in EEG data processing), did not include channels previously marked for interpolation and were filtered between 1 and 20Hz (using *eegfiltnew* function, which applies a Hamming windowed sinc FIR filter. High-pass and low-pass filters were applied separately. High-pass 1Hz order = 1650; low-pass 20Hz order = 166). ICA was applied only on recordings from the control video state (VD). This choice was made to be able to clearly identify saccades and blinks across all experimental states while allowing for faster calculations. Resulting ICA matrices were then applied to the original raw data of each experimental state within a single session. Subsequently, ICA components reflecting the activity caused by blinks and saccades were rejected. Despite the 1Hz initial filter, slow frequency artifacts ("drifts"), presumably due to increased sweating caused by the threat-induction procedure, were affecting the final ERP waveforms. As an additional step, we applied a high-pass 2Hz filter (2Hz, filter order = 414) on the ICA corrected data, successfully removing those artifacts. Bad channels were interpolated and the *Cleanline* algorithm was applied to remove 50Hz noise. Finally, epochs were generated for standard and deviant stimuli (-200 to 500ms after stimulus onset) and baseline-corrected (-100ms baseline). Epochs that included artifacts were removed by means of visual inspection. Visual inspection

was complemented by an automatic rejection of those epochs that included data points exceeding a $\pm 70 \mu\text{V}$ amplitude threshold. Epochs of data from one block were removed if the number of deviants in the safe or threat condition was lower than thirty-five after rejection of bad epochs. Based on this criterion, all data from one expert practitioner and data from specific experimental conditions (FA, OP, VD) and blocks were excluded from further analysis (see Supplementary Information 1.1 for a summary table and Supplementary Information 1.2 for a summary of the mean number of epochs in each session separately for group, state and stimulus type. Available online at osf.io/3f9e7). Outer ring channels were rejected for all participants due to occasional high-frequency noise caused by muscle-related artifacts identified in some subjects, (see Figure S1 for a visual layout of the remaining 41 channels. Available online at osf.io/3f9e7). Finally, a low-pass filter of 20Hz was applied to the epoched data for the analysis of the evoked responses.

2.5.1 Mismatch negativity

To identify the MMN, we computed the difference waveforms from the grand average between all subjects, separately for each group, state (FA, OP, VD) and session. We conducted the analysis using an a priori region of interest (ROI) which included the electrode Fz and four surrounding electrodes (figure S1). This ROI was in line with our previous research (Fucci et al., 2018) and with the literature on auditory MMN (e.g., Duncan et al., 2009). The MMN amplitude was computed based on a 20ms time-window centered around the most negative peak, between 90 and 200ms after stimulus onset, of the difference waveform for each session, state and group (in line with previous studies, e.g., Näätänen et al., 2004).

2.5.2 Alpha spectral power

For spectral analysis, we limited the analysis to two spatial regions of interest (ROI), frontal and occipital, defined similarly to Fucci et al., 2018 (see Figure S1 for a description of channels

included in the ROIs. Available online at osf.io/3f9e7). Cleaned epoched data were imported into MNE-Python (Gramfort et al., 2013) and power spectral density (PSD) was computed for each state (FA, OP and VD) and epoch with the multitapers method (Percival et al., 1993), using defaults parameters of the `psd_multitapper` function from MNE-Python (version 0.22.1). PSDs were then averaged across all channels of a ROI and alpha absolute power was computed as the integral approximation of the spectrum between 8 and 12 Hz using Simpson's rule (*simps* function from *scipy* 1.4.1, Python 3.8). Finally, alpha power was averaged for every subject across all epochs (deviants and standards), states and sessions, and log-transformed before statistical analyses.

2.6 Statistical analysis

R Studio (version 3.4.2 [R core team, 2017]) was used for all statistical analyses. R code used in the analysis can be found at osf.io/3f9e7.

2.6.1 Statistical Power

The present study was part of the ERC-funded, Brain and Mindfulness project (Abdoun et al. 2018). In the context of this larger multimodal, neurocognitive project, multiple factors determined the final sample sizes, independently of the goal of the current research (i.e., the estimation of meditation effects on the MMN). Nonetheless, our sample size is larger than any other used in previous, similar studies, including Fucci et al. (2018). We evaluated the statistical power of our current sample through simulations performed using the R library *simr* (v1.0.5; Green & MacLeod, 2016). Simulations were based on all model estimates (fixed and random effects) from Fucci et al. (2018) study. The variance of residuals was scaled up to take into account the fact that less trials were available to calculate the average ERP (112 deviant stimuli per state in the current study vs. 150 in Fucci et al. 2018). Two different values were explored

for the effect size of interest, namely the group by state interaction: the original effect size from the 2018 study, as well as half of it. Using 10,000 simulations for each scenario, we found that our replication analysis had 89% power to detect the original effect size, but only 33% to detect half of it.

2.6.2 Linear Mixed Models

We used linear mixed-effects models (R package *lme4*, Bates et al., 2014) to test the effect of group and state on the MMN amplitude and on the alpha log power separately (for alpha log power the analysis was performed independently for parietal and occipital regions of interest). For every model, group, state and their interaction were included as fixed effects and subject was included as random intercept. All models included unaveraged data from the two experimental sessions. The main effects and interactions of the model were estimated using a type III F-test with Satterthwaite's method for approximation of degrees of freedom. Paired t-tests, corrected for multiple comparisons using Tukey honestly significant difference test (HSD), were used as post-hoc tests comparing estimated marginal means using the R package *emmeans* (Lenth et al., 2020). In the results section, we report estimates of pseudo- R^2 as proposed by Nakagawa & Schielzeth (2013) for the full models and unstandardized effects sizes (pairwise differences in estimated marginal means and their associated confidence intervals) for pairwise comparisons. Notice that the computation of effect sizes in linear mixed models is not unambiguous and should be handled with consideration.

2.6.3 Bayesian Statistics

Model structure. The MMN amplitude was reanalyzed in the Bayesian framework using the R package *rstanarm* (v2.21.1; Goodrich et al., 2020). Data from the original experiment (Fucci et al., 2018) and the present study were modeled together within a single statistical model, the same used for frequentist analysis (see section above), with the minor addition of a fixed main

effect of Experiment to account for differences in recorded MMN amplitude due to differences in stimuli properties and recording devices. Interestingly, the Bayes factors obtained from a model combining two experiments is equal to the product of the Bayes factor obtained from the first experiment, by the Bayes factor obtained from the second experiment where the posterior distributions of the first experiment are used as priors of the replication (Ly et al., 2019):

$$\text{BF}(\text{exp}_1, \text{exp}_2) = \text{BF}(\text{exp}_1) \times \text{BF}(\text{exp}_2 | \text{exp}_1)$$

Prior distributions. We followed the principled Bayesian workflow proposed by Schad et al. 2021 to define priors that are compatible with domain expertise (see Supplementary Information 2 at osf.io/3f9e7). Prior predictive checks revealed that the default, weakly informative priors of *rstanarm* were unrealistic as they were compatible with highly implausible datasets. Therefore, we used an alternative set of narrower priors that remain broad enough to reflect very general and uncontroversial elements of domain expertise regarding the MMN component, *i.e.*, **knowledge about the likely characteristics of the MMN component obtained from previous research** such as plausible ranges of amplitude and effect sizes. Notably, all priors for the regression coefficients were normally distributed, centered on 0 (except the prior for the intercept, which was centered on the mean of the data). Standard deviations of normally distributed priors (regression coefficients) and rates of exponentially distributed priors (random intercept and residual variance) were conveniently set to 2 and 1 μ V, respectively.

Statistical inference. 10,000 samples were drawn from every posterior distribution. Contrast samples were extracted using the R package *emmeans* (Lenth et al., 2020). Bayes factors and support intervals were calculated using the R package *bayestestR* (v0.11.0 Makowski et al., 2019).

3. Results

3.1 MMN amplitude

3.1.1 Frequentist analysis

Here we sought to replicate previous findings on the different modulation of the MMN amplitude by meditation states and expertise. Figure 1.A shows the time-course of the mean difference waveforms, across participants and sessions during FA, OP and VD, separately for expert and novice participants. Figure 1.B shows the respective scalp topographies of the mean MMN peak amplitude for the above-mentioned states and groups. We did not find a significant interaction between group and state on the MMN amplitude ($F(2) = 0.51$; $p = 0.6$) [Figure 3.C; Pseudo- R^2 (full model) = 0.08, Pseudo- R^2 (fixed effects only) = 0.01]. A main effect of state or group was not present either ($F(2) = 0.57$; $p = 0.57$ and $F(1) = 1.95$; $p = 0.17$ for state and group, respectively). Additionally, we tested an alternative model at the frontal ROI which included MMN amplitude measures derived from the mean value in a fixed time-window of 90-180 ms after stimulus onset (in line with Fucci et al., 2018). Both models did not highlight any significant interaction or main effect of state and level of expertise.

When adding session information as a factor, the main model yielded a statistically significant main effect of session ($F(2) = 4.68$; $p = 0.03$; higher MMN amplitude during the second session). However, adding this factor did not influence the other results.

3.1.2 Bayesian analysis

Traditional frequentist statistical tests yield limited information and are inconclusive by nature when they fail to reject the null hypothesis. In contrast, Bayesian factors provide a measure of relative likelihood of two competing hypotheses and may be used to assess the evidence in

favor or against the null or a theory's predictions (Dienes, 2014). Moreover, calculating Bayesian factors on aggregated data naturally integrates the evidence provided by an experiment and its replication, where the inference of the replication builds on the conclusions of the original study (Ly et al., 2019). We have used this property to assess the accumulated evidence of our original study (Fucci et al. 2018) and the current replication, integrating the two studies in a single statistical model fitted and evaluated in the Bayesian framework. We focused on five effects of particular interest: i) the difference in MMN amplitude between states in experts compared to novices, which was the main finding of the original study; ii) the increase of MMN during FA as an effect of expertise, which is the most commonly reported result in the literature on meditation and MMN; the somewhat less studied iii) state effect of FA meditation (compared to a control condition) on MMN, here evaluated across all participants. Additionally, and in a more exploratory fashion, we tested iv) the effect of expertise on the MMN during the practice of OM/OP, as well as v) the main effect of OM/OP meditation across all participants. The posterior distributions of the five tested contrasts are represented in Figure 2 (top plots) along with the mean, 50% and 95% confidence intervals. For each contrast, hypothesis testing was carried out using Bayesian factors in two different ways. First, and following a common practice, we evaluated the evidence *in favor (or against) the null hypothesis BF_{01}* , compared to the alternative hypothesis that there is an effect of unspecified sign. This measure is particularly useful to reject the null hypothesis when it is true, but it is poorly informative when the evidence in favor of the null is not overwhelming (or even against it) as it says nothing about the direction and magnitude of plausible effect sizes. Therefore, we also report the range of effect sizes that received strong ($BF > 10$) evidence from the data, alias the *support interval* (Wagenmakers et al., 2020). Figure 2 summarizes the results, with the plots on the bottom row displaying the BF for the null hypothesis (i.e., BF_{01}) along with the $BF > 10$ and $BF > 3$ support intervals.

For the interaction effect between levels of expertise and meditation states, we found strong evidence in favor of the null ($BF_{01} = 11.0$) compared to the alternative hypothesis of a differential effect of meditation states on MMN between novice and long-term practitioners. Accordingly, the range of absolute effect sizes supported by strong evidence ($BF > 10$) extended in both directions around 0, from -0.05 to 0.25 μV .

For the expertise effect in FA, we found moderate evidence in favor of the null ($BF_{01} = 7.9$) compared to the alternative hypothesis of a difference in MMN between novice and long-term practitioners. Absolute effect sizes supported by strong evidence ($BF > 10$) ranged from -0.48 to -0.08 μV , corresponding to Cohen's d from 0.06 to 0.33 for a larger MMN amplitude in experts than novices.

For the state effect of FA compared to the control condition across all participants, the combined data provides strong evidence in favor of the null ($BF_{01} = 16.1$). Absolute effect sizes supported by strong evidence ($BF > 10$) ranged from -0.15 to 0.21 μV , an interval that is roughly centered on 0.

For exploratory purposes, we extended main effects analyses to the practice of OM/OP. We found moderate evidence in favor of a null effect of expertise ($BF_{01} = 5.3$; support interval = [-0.55 μV , -0.16 μV] corresponding to Cohen's d from 0.09 to 0.31 for a larger MMN amplitude in experts than novices), and stronger evidence in favor of a null effect of state ($BF_{01} = 11.9$; support interval = [-0.31 μV , 0.02 μV]).

Taken altogether, the results from the Bayesian reanalysis of 96 participants suggest a) that meditation expertise does not interact with meditation states with respect to the MMN amplitude; b) that extended lifetime meditation experience is unlikely to be associated to enhanced MMN component during meditation states and, if it does, it is to a small extent at best;

and c) that state effects of meditation on the magnitude of the MMN, if they exist, are even smaller than expertise effects.

3.2 Alpha spectral power

Investigation of spectral power differences in the alpha frequency band (8-12 Hz) was carried out across expertise groups and meditative states, for two spatial ROIs: frontal and occipital (figure S1). Results were similar in both ROIs (figure 3): there was no interaction between group and state [frontal ROI: $F(2) = 2.6$, $p = 0.076$, pseudo- R^2 (full model) = 0.84 (fixed effects only = 0.05); occipital ROI: $F(2) = 2.68$, $p = 0.07$, pseudo- R^2 (full model) = 0.86 (fixed effects only = 0.04)], and no main effect of group [frontal ROI: $F(1) = 1.1$, $p = 0.30$; occipital ROI: $F(1) = 0.63$, $p = 0.43$] but a main effect of state [frontal ROI: $F(2) = 35.9$, $p < .001$; occipital ROI: $F(2) = 44.4$, $p < .001$]. Post-hoc tests revealed higher alpha power during focused attention (FA) and open presence (OP) meditations compared to the video control state (VD) (frontal ROI: VD-FA t-ratio(306) = -5.8, $p < .001$, estimate = -0.21 [-0.29, -0.12], VD-OP t-ratio(307) = -8.2, $p < .001$, estimate = -0.3 [-0.38, -0.21]; occipital ROI: VD-FA t-ratio(306) = -6.7, $p < .001$, estimate = -0.29 [-0.39, -0.19], VD-OP t-ratio(306) = -9.1, $p < .001$, estimate = -0.4 [-0.5, -0.29]) and also during OP compared to FA meditation (FA-OP, frontal ROI: t-ratio(306) = -2.47, $p = .037$, estimate = -0.089 [-0.17, 0]; occipital ROI: t-ratio(306) = -2.40, $p = .040$, estimate = -0.1 [-0.21, 0]). **Notice that the higher alpha power observed during meditation states compared to the control condition could be due to differences in visual stimulation (i.e., a video stimulus versus a fixation cross). This issue is discussed in section 4.4.**

4. Discussion

4.1 Frequentist analysis: non replication of meditation states and expertise effects on MMN amplitude

In the present study, we sought to replicate previous findings on the differential modulation of the auditory MMN amplitude by meditation states in novice and expert practitioners, as observed in Fucci et al., (2018). The replication attempt was conducted in the context of a similar, although not identical, experimental paradigm, using the same frequentist models for statistical analysis and with a high enough statistical power to detect the effects reported in Fucci et al. (2018). As a result, we did not find any statistically significant interaction effect between meditation states and groups, nor differences between groups or states taken independently (figure 1). This result was unexpected because previous research has shown an impact of meditation on the auditory MMN amplitude. Different studies reported increased MMN amplitude during FA meditation as a state effect in experts or novice practitioners (Braboszcz and Delorme, 2011; Srinivasan and Baijal, 2007) or as a trait effect in experts compared to novices (Biedermann et al., 2016; Srinivasan and Baijal, 2007), while one study reported increase MMN amplitude during FA in experts, compared to novices, but no difference between a control condition and a state of nondual, open presence (OP) meditation (Fucci et al., 2018).

The non-replication of previously reported results could be related to factors undermining research replicability in the field of contemplative science and in the broader fields of cognitive neuroscience and experimental psychology. First, previous studies were conducted on sample sizes that are likely inadequate to detect reasonable effect sizes (Srinivasan and Baijal, 2007 $n = 10$ [experts] and $n = 10$ [novices]; Braboszcz and Delorme, 2011 $n = 12$; Biedermann et al., 2016 $n = 12$ [experts] and $n = 14$ [novices]; Fucci et al., 2018 $n = 16$ [experts] and $n = 15$ [novices]). Low statistical power is a well-known issue affecting neuroscientific studies (Button

et al., 2013). It can not only reduce the chance of detecting moderate and low effects, but also increase the likelihood that statistically significant differences overestimate (Gelman & Carlin 2014) or do not represent true effects (in this case affecting the positive predictive value [PPV], which is the probability that a “positive” finding represents a true effect; Ioannidis, 2005). These issues are reinforced by the selective reporting of positive findings (so-called “publication bias”). Secondly, some of the previous studies implemented analysis approaches that deviates from standard practices without a strong methodological justification. For instance, Biedermann et al. (2016) reported increased MMN amplitude in experts, compared to novice practitioners at Pz electrode. This is an unconventional scalp area for the analysis of the auditory MMN amplitude, which normally peaks at frontocentral scalp regions (Naatanen et al., 2011). In Srinivasan and Baijal (2007), increased MMN amplitude during a form of FA meditation in expert practitioners was reported following a post-hoc analysis carried out specifically on this group. However, since no interaction between groups and meditation states was present in the main model tested, the validity of the post-hoc analysis is questionable. More generally, the high degree of flexibility characterizing analysis in neuroscientific studies is prone to increase the chance of false positives (Gelman & Loken, 2013; Poldrack et al., 2017).

Together with small sample sizes, these issues could have increased the prevalence of Type I errors in the research on MMN modulation by meditation states and traits and could represent an explanation for the discrepancy between the null findings reported in the present study and the previous literature. The participants sample studied here was at least double the size of those used in previous research and allowed for the detection of an effect as large as the one reported in Fucci et al. (2018) with a 89% power. Overall, the present study represents, in our opinion, the most reliable analysis of the modulation of auditory MMN by meditation states and traits to date.

This is the first report of null findings on this subject. However, it could be the case that other studies did not report null results on the influence of meditation on the MMN amplitude or did not analyze the MMN component in auditory oddball paradigms. While trying to make sense of the differences between our null findings and the existing literature, we identified at least seven studies that implemented similar experimental designs (i.e. passive or active auditory oddball tasks with tones presented binaurally), groups of participants and meditation practices (Atchley et al., 2016; Barnes et al., 2018; Cahn & Polich, 2009; Delgado-Pastor et al., 2013; Isbel et al., 2019; Klee et al., 2020; Yoshida et al., 2020). They reported results of analyses on auditory event-related EEG components, but not on the MMN amplitude even though this was feasible. We contacted the first and corresponding authors of these studies to ask whether they had the opportunity to analyze the MMN component. Up to date, only the authors of Cahn and Polich (2009) replied, saying that no difference in MMN amplitude was found between FA meditation and a control state in expert practitioners in their study. This adds one element to the list of null findings on the subject of MMN modulation by meditation states and traits. Formally estimating whether the literature on this topic is significantly affected by selective reporting was beyond the scope of the present study, but there are reasons to believe that it could be the case. Publication bias is highly prevalent in psychology and social sciences (Fanelli, 2010) and it has been recently identified in the context of mindfulness-based interventions research (Coronado-Montoya et al., 2016).

4.2 Bayesian analysis of accumulated evidence: assessing the likelihood of meditation state and trait effects on the auditory MMN

Frequentist analyses have failed to reject any null hypothesis pertaining to the effect of meditation states or expertise on the amplitude of the MMN, prompting the use of Bayesian measures of evidence to quantify the support for such null hypotheses. We focused in particular

on the interaction between meditation expertise and meditation states, as well as on simple effects of expertise during meditation states, and main effects of meditation states across all participants.

First, we found that the effect of expertise during FA meditation, which has been reported multiple times in the literature (Srinivasan and Baijal 2007, Biedermann et al., 2016, Fucci et al., 2018), was in the expected direction - i.e., larger MMN amplitude for expert meditators - but compatible with null effects and moderate at best. A similar conclusion could be drawn for OM/OP meditation. Second, the aggregated data provided strong evidence in favor of an absence of meditation (both FA and OM/OP) state effects across participants and levels of expertise, as well as an absence of interaction between meditation expertise and meditation states with respect to the MMN. The same conclusions were reached using Bayes Factors and hypothesis testing based on posterior distributions. Overall, these findings disqualify the auditory MMN as a marker dissociating meditation states from the FA and OM families, or even meditation states from baseline conditions. Our data remain compatible with the theory that meditation practices impact perceptual learning, especially in experienced practitioners, but they suggest that the size of effect is too modest for the MMN amplitude to be a practically useful index of meditation state and/or expertise. Future research on this topic may benefit from the development of more sensitive biomarkers, potentially driven by theoretical considerations on the phenomenology of meditation states.

4.3 Modulation of alpha spectral power by meditative states and expertise

Consistently with previous literature (Cahn & Polich 2006, Lomas et al. 2015 and Lee et al. 2018), we observed an increase in the power of alpha (8-12 Hz) EEG oscillatory activity during focused attention (FA) and open presence (OP) meditations, compared to a control state, in both frontal and occipital scalp regions and for both expert and novice practitioners. This partially replicates findings on oscillatory power from Fucci et al. (2018), with the addition of

a significant difference between FA and OP in both frontal and occipital ROIs that was only present as a trend in the previous study. This last result should be taken cautiously due to its relatively small effect size compared to the larger difference between meditation and control conditions.

Even when increasing the sample size compared to our previous study (Fucci et al. 2018), we did not find differences in alpha power between groups (experts vs novices). This null finding is in contrast to previous research where trait effects were observed (see Cahn & Polich 2006 for a detailed review). As pointed out in a recent opinion paper (Schoenberg et al., 2018), one must be careful when interpreting results from a single measure of frequency band power to avoid oversimplifying the multi-dimensionality of meditative states that are known to be phenomenologically very complex (Lutz et al. 2015). Increased alpha power has notably been linked to breath-control (Zaccaro et al., 2018) and sustained and selective attention processes in the visual (Clayton et al., 2015; Foxe & Snyder, 2011; Klimesch, 2012) but also auditory modality (Strauß et al., 2014; Weisz & Obleser, 2014). While meditation practices are likely to affect these processes (Gerritsen & Band, 2018; Kerr et al., 2013), most paradigms and analyses from the literature, including ours, do not allow to clearly disentangle them. Overall, due to the lack of specificity and unclear functional explanations concerning the engagement of alpha power in meditation, we would suggest not to rely on this marker alone to characterize meditative states and traits; a warning already raised by Cahn and colleagues (Cahn et al., 2010). Thus, we would like to emphasize that more advanced analyses involving compositional markers are needed to fully depict the diversity of attentional and perceptual processes at stake during contemplative practices and how they are shaped by long-term training. Examples of novel analyses of brain oscillatory activity during meditation can be found in the recent literature (Rodriguez-Larios et al., 2020; Schoenberg et al., 2018; van Lutterveld et al., 2017).

4.4 Limitations

The present study is affected by some limitations that might deserve further investigation. First, the non-replication of our previous findings might have been influenced by differences in the experimental design between the present and our previous study: Fucci et al. (2018) used a random inter-stimulus interval (I.S.I.) normally distributed between 800 and 1200ms, while we used a shorter and fixed one of 500ms (consistently with previous literature in the field of auditory MMN, e.g. Näätänen et al. [2004]). Additionally, in our previous study novices received only a meditation instruction before the task while in the present study they underwent an introductory practice weekend and practiced daily before the experiment (see Abdoun et al. 2018). Enhancing the meditative skill of novices could have decreased our ability to detect a group by state interaction but would have **increased the study's potential for detecting a state effect**. Moreover, participants underwent short oddball sequences embedded in safe or threat periods. Previous studies on MMN modulation by meditation states and traits did not explore this marker in the context of mood induction. Here, we excluded data acquired during periods of threat, which were separated from neutral periods by a pause of several seconds. In a separate report (Fucci et al., 2019), we describe subjective and electrophysiological responses to the different periods in novice practitioners during a control state, showing how they can be independently characterized and how threat periods do not seem to influence the MMN amplitude. However, it is possible that emotional contexts masked effects that would otherwise be present in a neutral situation through a lingering effect.

Secondly, our studies made use of the classical, simple oddball task and our conclusions are restricted to that specific class of experimental designs. In particular, our data and analyses do not exclude the possibility that meditation alters perceptual or statistical learning in more elaborate settings.

Thirdly, the critical literature review included in the discussion section of the present study cannot be considered as reliable as a meta-analysis. No formal approaches have been implemented to determine the prevalence of a publication bias in the literature. As such, the explanations for the non-replication proposed in the discussion section should be considered as opinions informed by an empirical approach rather than statements derived from formal analyses.

Concerning the results on alpha oscillations, as suggested by one reviewer, we cannot entirely exclude that the modulation of alpha power between experimental conditions was partly due to differences in visual stimuli (silent movie for VD and fixation cross for FA/OP). Nonetheless, the results of the present study are supported by the difference found between meditation styles involving the same visual stimuli. We also acknowledge that the current design and analysis, replicating Fucci et al., (2018), do not allow us to disentangle the effects of meditation from the effects of the oddball task and their interaction on alpha power. Finally, a reviewer pointed out that differences in alpha power, interpreted as change in the periodic component of oscillatory activity, could also be due to a confounding difference in aperiodic components (1/f like, for example offset and slope). We visually inspected the spectral power density distributions to make sure that the differences in alpha power were not conflated by such aperiodic activity (see Supplementary Figure S3). However, more rigorous methods exist to differentiate periodic and aperiodic components (Donoghue et al. 2020) and they will be worth using in future analyses.

4.5 Future directions

In conclusion, while the MMN is a robust ERP component and reliable neural correlate of attentional processes and perceptual inference in the sensory domain, we warn about its use to

back up models of meditation influence on attention and perceptual inference until there is more clarity on the effects of expertise and practices on this marker. Future studies on this subject should design adequately powered experiments and implement rigorous and standardized methods of analysis (or justify alternative methods with valid arguments). To support this, we encourage pre-registrations of both new experiments and future replication attempts (Nosek et al., 2019). Replications of existing studies and reporting of null findings should be a priority for neuroimaging investigations of contemplative practices and recent publications suggest that this field might not be unaffected by the general replicability crisis in neuroscience and psychology research (Barnes et al., 2018; Payne et al., 2019). Additionally, future studies could implement recent analysis approaches in the Bayesian framework to determine the validity of initial hypotheses and produce estimates of plausible effect sizes for a given effect of interest. Future exploratory research could also benefit from electrode-wise cluster-based methods of analysis to identify possible effects in unconventional scalp regions and time windows, **as well as from recent developments in EEG data processing that address limitations in the use of baseline correction and can determine how much this step contributes to observed differences in post-stimulus ERPs (Alday, 2019).**

Finally, refining the phenomenological granularity of meditation instructions, for instance comparing FA on the auditory sounds to FA on a visual distractor **(or to the widely practiced FA on bodily sensations)** during auditory oddball paradigms could also deepen our understanding of these processes.

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6. Contributions

EF and AL designed the experiment. EF collected data. EF, OA and APC analyzed data. EF, OA, APC and AL wrote the manuscript.

7. Data availability statement

Single-subject preprocessed EEG data (MMN amplitude and alpha power) used for statistical analysis are available, along with analysis code, at a repository of the Open Science Framework (osf.io/3f9e7). The repository also contains single-subject MMN amplitude data from Fucci et al. (2018), which was used when conducting analysis in the Bayesian framework. The manuscript contains detailed information that should allow a replication of the findings. If you would like to obtain raw EEG data, or need further information, please contact the corresponding author. The experiment was not preregistered.

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Figures captions

Figure 1. Meditation states and degrees of experience do not modulate the amplitude of auditory mismatch negativity (MMN). (A) Subtraction (deviant minus standard, i.e., MMN) waveforms at frontal ROI (see fig. S1) for FA, OP and VD states (FA: focused attention meditation, OP: open presence meditation, VD: watching a silent movie) in expert (top) and novice (bottom) practitioners. (B) Average voltage scalp maps of MMN in a 20ms window centered around the peak amplitude [between 90 and 200ms after stimulus onset] for experts (top) and novices (bottom) during FA, OP and VD. (C) Box plots and half-violin plots displaying median values and distribution of the MMN peak amplitude averaged over sessions across subjects at frontal ROI.

Figure 2. Bayesian analysis of aggregated data provides evidence for null effects of meditation states and expertise on the MMN. Data from Fucci et al. 2018 and the current study were fitted in a single model to assess the cumulative evidence obtained from the original study and its replication. Labels at the top indicate the contrasts that have been tested, with “A > B” meaning “A minus B”. (Top) Posterior distributions of contrasts of interest. Thick and thin lines represent 50% and 95% highest density intervals respectively. (Bottom) Bayes factors of point hypotheses. For each value δ , BF_{δ} is the Bayes factor of the hypothesis that the absolute effect size of the contrast (i.e., its amplitude in μV) is equal to δ vs. the alternative,

complementary hypothesis that it is different from δ . Note that BF01, the Bayesian factor of the null hypothesis, is the special case of $\delta=0$. Light and dark shaded areas highlight the support interval for $BF>3$ and $BF>10$, respectively, i.e., values of the contrast estimate that receive substantial and strong evidence, respectively, from the data when pitted against the alternative, complementary hypothesis. The null hypothesis falls within the substantial support interval for expertise effects during FA and OM (second and fourth plots, respectively) and within the strong support interval for all other tested contrasts.

Figure 3. Increased alpha power in two different meditation practices compared to a control state. Box plots and half-violin plots displaying median values and distributions of alpha (8-12Hz) log spectral power averaged over sessions at frontal (left) and occipital (right) ROIs for FA, OP and VD states in expert (dark shade) and novice (light shade) practitioners. Statistical analyses revealed significant main effects of state in both ROIs regardless of expertise, with FA and OP showing higher alpha than VD (*: $p < 0.05$, ***: $p < 0.001$, p-values from post-hoc tests of linear mixed models).

A

B

C

Posterior distribution

Bayes Factor