An #EEGManyLabs study to test the role of the alpha phase on visual perception

(a replication and new evidence)

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Competing Interests:
The authors disclose no conflicts of interest related to this manuscript.

Funding:
#EEGManyLabs is supported by a DFG (PA 4005/1-1) grant to YGP and a UKRI BBSRC grant (BB/X008428/1) awarded to FM.
The Lead Replicating lab (BCBL, Author#MR, Author#NM, Author#JPN, Author#PM, Author#SN) is supported by the Basque Government through the BERC 2022-2025 program and by the Spanish State Research Agency through the Severo Ochoa excellence accreditation CEX2020-001010-S.
Author #MR is supported by Ministerio de Ciencia e Innovación (MICIIN) and the Agencia Estatal de Investigación (AEI) under the Ramón y Cajal program (RYC2019-027538-I/0.13039/501100011033).
The Basque Foundation for Science (Ikerbasque) supports both Author#MR and Author#NM.
Author #NM is supported by the Agencia Estatal de Investigación (AEI) under the grants RTI2018-096311-B-I00, PDC2022-133917-I00, PCI2022-135031-2 and PID2022-136991NB-I00.
Authors #SSF and #MTC are funded by Ministerio de Ciencia e Innovación (MICIN) under the grants PID2022-137277NB-I00 AEI/FEDER and PDC2022-133859-I00, and by AGAUR, Generalitat de Catalunya under the grant 2021 SGR 00911.
Replicating Lab author #AMH is supported by an Australian Research Council (ARC) Discovery Early Career Researcher Award (DE220101019).
Replicating Lab author #BNJ is supported by an Australian Research Council (ARC) Discovery Early Career Researcher Award (DE220100739).Replicating Lab author #MK is funded by an SGSSS (UKRI ESRC: ES/P000681/1) stipend awarded to authors CB and #CK.
Replicating Lab author #AZ is funded by the Italian Ministry of Health (‘Ricerca Corrente’).
Replicating Lab author #JS has no funding to report for this work.
Author#PM received support from “la Caixa” Foundation (ID 100010434) through the fellowship LCF/BQ/IN17/11620019, and the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement no. 713673.
Replicating Lab authors #DB and #LF are supported by the “Project Departments of Excellence 2023-2027” (IN2DEPT Innovative and Integrative Department Platforms) awarded by the Italian Ministry of University and Research.

The funders had no role in the study design or the decision to submit the work for publication.

Abstract

Several studies have suggested that low-frequency brain oscillations could be key to understanding how the brain samples sensory information via rhythmic alternation of low and high excitability periods. However, this hypothesis has recently been called into question following the publication of some null findings. As part of the #EEGManyLabs initiative, we set out to undertake a high-powered, multi-site replication of an influential study on this topic. In the original study, Mathewson et al. (2009) showed that during high amplitude fluctuations of alpha activity (8-13 Hz), the visibility of a visual target stimulus depended on the time the target was presented relative to the phase of the pre-target alpha activity. Furthermore, visual evoked potentials (e.g., N1, P1, P2 and P3) were larger in amplitude when the target was presented at the pre-stimulus alpha peaks, which were also associated with higher visibility. If we are successful in replicating the results of Mathewson et al. (2009), we intend to extend the original findings by conducting a second, original, experiment that varies the pre-stimulus time unpredictably to determine whether the phase-behavioural relationship depends on the target stimulus having a predictable onset time.

Introduction

Brain rhythms reflect cyclic fluctuations in neural excitability (Bishop, 1932; Buzsáki & Draguhn, 2004; Doelling & Florencia Assaneo, 2021), which are thought to play a role in how sensory information is processed (Schroeder & Lakatos, 2009). Low-frequency brain rhythms have been hypothesised to chunk sensory input into consecutive snapshots, like neural shutters (Adrian & Matthews, 1934; Poeppel, 2003; VanRullen, 2016; Walter, 1950). This means that information presented at specific times (i.e., phases) in relation to the ongoing oscillations may be processed differently, as measured by physiological (e.g., ERPs) and/or behavioural (e.g., sensitivity, reaction times) indices (Başar et al., 1997; Callaway, 1962; Dustman & Beck, 1965; Harter, 1967; Lindsley, 1952; Samaha et al., 2020; VanRullen, 2016).

The possibility that perception and cognition operate in cycles, following brain rhythms, has attracted researchers' interest for decades because it offers a unifying account of how brain oscillations contribute to prioritizing, categorising, and manipulating sensory input to provide accurate and fast responses to relevant stimuli. In addition, if brain rhythms and behaviour share an oscillatory "*modus operandi*", it may be possible to influence or control one (i.e., via entrainment) to change the other (Callaway & Yeager, 1960; Vigué-Guix et al., 2022; Vigué-Guix & Soto-Faraco, 2023; Zrenner et al., 2018). This would allow scientists to study how the brain processes information more directly and devise new interventions.

Yet, despite almost a century of research, the role of low-frequency oscillations (5 - 13 Hz) in perception remains a topic of debate with mixed evidence (Keitel et al., 2022; Melcón et al., 2023). Several methodological issues playing a part in this have been identified. First, many EEG experiments investigating the role of pre-stimulus oscillatory phase on visual target detection allow a large number of analytical degrees of freedom that can undermine statistical power. Second, effect sizes for positive findings are typically small (e.g., phase differences account for 10-20% of the variability in behavioural performance for visual detection tasks; VanRullen, 2016), as are the sample sizes employed in many studies (see Table 2, in Ruzzoli, Torralba et al., 2019); therefore, the reliability and replicability of many positive findings remain unknown. Finally, negative findings are unattractive to the publication process and thus subject to the file drawer problem (but see Keitel et al., 2022). These issues are intrinsic to many brain imaging studies and undermine progress in neuroscientific research. The #EEGManyLabs initiative (Pavlov et al., 2021) offers one solution to these issues, through replicating influential EEG studies across multiple labs under similar experimental conditions. The first goal of the present research is to contribute to the #EEGManyLabs initiative by providing an exact replication of an influential paper on the role of pre-stimulus phase effects for discrete perception (Mathewson et al., 2009).

To test the hypothesis that visual perception fluctuates rhythmically as a function of the pre-stimulus phase of alpha oscillations (8-13 Hz), Mathewson et al. (2009) used a detection task of a central, masked target presented 400 ms after the appearance of a fixation cross. The authors sorted the trials based on the median value of the pre-stimulus alpha power and found that when alpha power was high, stimuli presented at the peak of the alpha cycle had a higher probability of being detected and elicited larger evoked potentials (e.g., N1, P1, P2 and P3). This finding aligned with the idea of brain rhythms as cycles of cortical excitability. In contrast, no phase effects were found when alpha power was low. Mathewson et al. (2009) proposed the *pulsed inhibition hypothesis*, according to which two mechanisms are involved in the inhibitory effect of the alpha

rhythm to facilitate stimulus processing (Klimesch et al., 2007; Worden et al., 2000). The first involves the alpha *power* in the relevant sensory cortex, which, if decreased, increases cortical excitability and facilitates stimulus processing. Second, when alpha power is high (therefore outside an attentional hotspot), target processing is affected by the *phase* at which the stimulus is presented along the alpha cycle (Mathewson et al., 2009, 2011). The combination of a simple paradigm, converging behavioural and ERP results, and the proposal of a plausible theoretical account has led this work to have a significant impact on the field.

One important aspect of Mathewson et al.'s (2009) study is the fixed delay (SOA) between fixation and target onset (400 ms), which has two significant consequences. First, it limits the time (-200 ms) and frequency (10 Hz) for the data analysis because the available pre-target time free of contamination due to the fixation onset is short. Second, the predictability of target appearance could have induced temporal expectations. This may have affected the pre-stimulus oscillatory phase and favoured the perception of the target, and thus biased the results towards a positive finding (Nandi et al., 2023; Samaha et al., 2015; but see Rohenkohl & Nobre, 2011 for negative findings). Indeed, if a target occurs at regular and constant intervals and is therefore highly predictable, the reported phase-behavioural effect might be driven by temporal expectations rather than being a spontaneous perceptual process, as originally hypothesized (Busch et al., 2009; Ruzzoli, Torralba et al., 2019; VanRullen et al., 2011). For example, in their registered report, Ruzzoli, Torralba et al., (2019) adopted a similar paradigm to Mathewson et al., (2009), but introduced a variable delay before the stimulus onset. Their results were inconclusive regarding cyclic modulation of perception, suggesting that temporal expectation might play a bigger role in the pulsed-inhibition hypothesis than originally considered. The temporal expectation potentially affects a number of studies in this area above and beyond Mathewson et al. (2009) (e.g., Harris et al., 2018; Myers et al., 2014; Samaha et al., 2015), and as such, addressing this issue could have a broader impact on the field. Thus, conditional to the successful replication of the results reported by Mathewson et al. (2009), our second objective is to build upon the multi-site approach (Pavlov et al., 2021) and perform an original experiment under identical experimental conditions following the same analytical pipeline as in Mathewson et al. (2009), except for the implementation of a variable SOA before the target onset. This will provide a more comprehensive understanding of the relationship between the oscillatory phase, behavioural responses, and temporal expectation.

In summary, this registered report sets out to clarify the role of low-frequency pre-stimulus phase in visual perception by collecting a large amount of data from multiple labs under similar controlled conditions in an exact replication of Mathewson's et al. study (2009) (Study 1). If the replication is successful (or inconclusive), we will undertake a follow-up investigation to study how temporal expectations contribute to phase-behaviour correlations in EEG research (Study 2).

Hypotheses

In the present RR, we will test two main hypotheses (see also Table 1 and Table 2):

a) If visual perception operates in cycles, then the moment at which a target is presented, with respect to the pre-stimulus brain rhythm in the relevant low-frequency bands, will affect stimulus processing, leading to behavioural (e.g., detection rate; Hp a.1, and a.2, Table 1) and/or electrophysiological (e.g., ERPs; Hp a.3, Table 1) effects. According to the *pulsed inhibition hypothesis* (Mathewson et al., 2009, 2011), these effects should be

evident (at least) when pre-stimulus alpha power is high (Hp a.1, Table 1). Alternatively, if behavioural and/or electrophysiological measures have no relation to the phase of the pre-stimulus, low-frequency brain rhythms, we should conclude that we do not replicate Mathewson et al. (2009) results; therefore, within the studied parameters, there is no evidence for visual perception to operate in cycles (see Table 2).

b) The second hypothesis states that if visual perception operates in cycles, then the influence of the pre-stimulus oscillatory phase on behavioural and/or neurophysiological measures should be valid regardless of whether temporal expectation is strong (Study 1) or weak (Study 2) (Hp b.1, Tables 1-2). Alternatively, if behavioural and/or neurophysiological phase effects are only evident (or bigger) in the fixed (vs. jittered) target onset, we should conclude that there is evidence for temporal expectation to operate in cycles, at least within the studied parameters; however, when expectancy is strongly reduced, phase effects are negligible.

Although the main hypotheses will be tested by replicating the statistics in the original study (Mathewson et al., 2009), we will consider the current replication a success if a statistically significant ($p<0.02$) meta-analytic estimate across labs is observed in the expected direction (Pavlov et al., 2021) (Hps a, only). Please note that although testing Hp-b is conditional upon Hp-a significance, it will not affect the replication attempt within the #EEGManyLabs project (see also Table 2).

Methods

We plan to run two studies, both testing the general hypothesis that low-frequency oscillatory phase influences visual detection and/or visual ERPs. Study 1 is a direct replication of Mathewson et al., (2009) in which the time before the target appearance is fixed. Study 2 will be undertaken only if we obtain positive (or inconclusive) results from Study 1, and it will adopt the same paradigm as Study 1 with the exception of a variable delay before the target onset.

Participants: 9 labs (see Table 3 for the labs involved) will provide an N= 35 participants each (age range: 18-30; with normal or corrected to normal vision) for Study 1, for a total of N= 315 participants. Additionally, if the Study 1 results are positive or inconclusive, 4 labs have committed to providing N=35 participants each for Study 2 (note that the number of labs involved in Study 2 may increase in later stages of the present RR; and the number of labs will be taken into account when comparing results from the two studies). Each lab will obtain ethical approval from their relevant institutions and a signed consent form from each participant, including the data-sharing option.

To estimate the sample size for Study 1, we proceeded as follows. For each hypothesis we will test in the present RR as a replication of the original study, we estimated a sample size value from the results reported in Mathewson et al. (2009) (see Table 1). The final sample size (N=35) is the maximum number among the single estimations. Specifically, for each of the hypotheses, we considered half of the computed effect size (Cohen's dz) from the original statistics and estimated the sample size through G*Power (ver 3.1.94; Erdfelder et al., 2009) as the number of participants needed to replicate the effect (if it exists) with 90% power and $p < 0.02$. For Study 2, no previous data are available to estimate a sample size; therefore, we decided to use the same sample size as for Study 1. Indeed, according to the null hypothesis (Hp b, as listed before), if pre-target temporal

jitter plays no role in the phase-behavioural correlation, then we expect similar phase-behavioural effects for Studies 1 and 2.

Stimuli and procedure: The experiment in both Studies 1 and 2 will consist of a masked visual detection task written in custom-made codes (see Table 3 for lab specifics). Stimuli will be presented on a monitor with a refresh rate of 85 Hz as in the original study (alternatively, a refresh rate of 100 Hz will also be accepted). The timing of the experimental flow is reported here in ms and in the related number of frames according to a 100 Hz screen refresh rate, which is the most used (see Table 3). For the original timing, using an 85 Hz refresh screen rate, we refer the reader to the original manuscript (Mathewson et al., 2009). In each trial, participants will look at a black fixation cross presented at the center of the screen on a uniform grey background for 250 ms (25 frames). After a 400 ms fixed Inter-Stimulus Interval (ISI) (Study 1, 40 frames) or a variable ISI (Study 2), a target can appear for one frame (10 ms). The variable ISI for Study 2 will be calculated as follows:

$$Delay = 400\,ms + x$$

Where x is a random delay extracted from an exponential distribution with a mean value of $\lambda = 150$ ms that can be described as, for $x > 0$

$$f(x) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}}$$

By using this specific distribution to generate ISIs, the temporal uncertainty is maximized while the hazard rate is constant for intervals 400 to 1000 ms. ISI longer than 5000 ms will be set to 5000 ms to prevent too long trials (note that this case will be extremely unlikely, as the probability of obtaining ISIs longer than 1500 ms with current distribution is 0.6%.

The target is a dark grey circle (1 visual degree at a distance of 57 cm) presented at the center of the screen. After a delay of 5 frames (50 ms) of a blank screen, a mask (outer annulus of 2 visual degrees) can appear for 2 frames duration (20 ms). There are three types of trials: 1) target-mask trials (in which both the target and the mask are presented), 2) target-only trials, and 3) mask-only trials. Half of the trials within each block will contain both a target and a mask, while 25% will be target-only, and the remaining 25% will be mask-only trials. Participants must report whether they saw the target in a maximum time window of 1520 ms (152 frames) after the mask (or the target, depending on the trial type) offset by pressing the Z (yes) or the N (no) key on the keyboard, with the left and right index fingers, respectively.

While Mathewson et al. (2009) decided to set a-priori the colour contrast of the target and mask used in the experiment, we will adjust it individually based on a 3-down/1-up staircase. This will make the entire procedure and participants' selection more reproducible and comparable across labs. The staircase starts from a clearly visible contrast value and decreases it by three steps after 3 consecutive correct responses or increases by four steps after one wrong response. The staircase stops after 21 reversals and takes as a threshold the mean value of the last 20 reversals (see García-Pérez, 1998 for a justification of the staircase parameters). In the staircase procedure, the proportion of trial types is maintained as described for the experimental session; however, for the threshold calculation, only target-masked trials will be considered. If the staircase does not converge after 144 trials (2 blocks of 72 trials), it will be aborted and repeated (if the number of repetitions is < 4; see below).

Instructions are provided by the experimenter and written on the screen in different languages depending on the lab. Participants are familiarized with the stimuli and the trial types with an example of 6 trials with varying trial types and target and mask contrast values. In the example, events (i.e., target and mask) are presented slowly. After the example, a practice session of 20 trials begins in which participants receive feedback (green/red fixation cross) after each response. In the practice session, the target and mask contrast are set to be easy to detect. Next, it follows a staircase session (max 144 trials) and a 72-trial validation session in which the threshold-contrast value is tested. A participant is invited to continue with the experimental session only if in the validation session 1) the d-prime is above 0; 2) the false alarm (FA) rate is <= 25% (the max FA in Mathewson et al., 2009 data); and 3) the hit rate (Hit) is between 20% (included) and 80% of the total amount of trials. If one or more of these criteria are not met, the staircase and the validation session will be repeated up to three times, after which the participant will be exonerated from the study, and the collected data will not enter the final analysis. Within each study, the main experimental session consists of 16 blocks of 72 trials each. Reaction times will be collected as complementary information, although we do not plan any RT analyses in the present RR.

Before running the experimental session and after the staircase-validation procedure, we will record resting EEG with alternating periods of eyes closed and eyes open (8 minutes overall) through a standardize procedure (see https://github.com/eegmanylabs/restingStatePresentation). A few labs will also collect responses to three personality questionnaires. Specifically, the Karolinska Sleepiness Scale (KSS; Åkerstedt & Gillberg, 1990), the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988), and the State-Trait Anxiety Inventory Trait Version (STAI-T Spielberger et al., 1970). This procedure serves two goals: 1) provide individual resting data for exploratory data analysis; 2) collect data for a #EEGManyLabs collateral project (Pavlov et al., 2021; see https://osf.io/sp3ck/). ***EEG recording***: In the original study, EEG data were recorded from 21 electrodes. In this RR, all labs will record data from more electrodes to allow for exploratory analyses of a large dataset and foster data re-usage. This deviation from the original study should not affect data quality or the results. All labs will make sure to include the channels needed to replicate the original analysis (i.e., Fz, Pz) and two electrodes placed on the left/right mastoid bones for offline re-referencing. Additionally, four electrodes for eye movements and blink detection will be used (two electrodes above and below the left eye and the other two placed at the outer of the eyes' canthi). The sampling rate will be 1024 or 1000 Hz depending on the EEG system used.

Analysis pipeline

Behavioural

As in the original study (Mathewson et al., 2009), behavioural data will be used to ensure participants are performing the task as expected. To this end, we will calculate and report 1) the individual and group average detection rate (i.e., the proportion of "yes" responses when the target has been presented, Hit) and related standard deviation (SD); 2) the individual and group average false alarm rate (i.e., the proportion of "yes" responses when the target has not been presented, FA) and related SD. We will also calculate and report the individual and group average d-prime and criterion values (± SD), calculated by Böckmann-Barthel's function (2023).

A participant showing an inappropriate behavioural performance will be excluded from a lab dataset and replaced by another one. Specifically, to admit an individual dataset in the final sample, the d-prime should be > 0, the FA < 25% and the Hit between 20% (included) and 80%.

Those criteria were decided based on Mathewson et al.'s original data (2009) to ensure that each participant performs the task as instructed and that the number of trials in the hit-and-miss conditions (before artefact rejection) is comparable.

At the behavioural level, we will also investigate the changes in performance at the block level to make sure EEG data entering the final dataset are meaningful. Indeed, it could be possible that the overall performance is within the limits described above, but the block-by-block performance fails (Ruzzoli, Torralba et al., 2019). However, block performance should not be too restricted. Therefore, we decided to add a further exclusion criterion compared to Mathewson et al.' (2009): if the FA rate is above 25% in a block, data from the entire block will be removed from the dataset.

Finally, we considered that the analysis of the previous trial type reported by Mathewson et al.', (2009) is not relevant to the goal of the present replication; therefore, we will not attempt to replicate it.

EEG

Pre-processing: Data will be analysed with Matlab and Fieldtrip (Oostenveld et al., 2011; http://fieldtriptoolbox.org). Continuous data will be band-pass filtered at 0.01-25 Hz using a two-pass-reverse filter as implemented in ft_preprosessing (bpfilter order = 1) in Fieldtrip (Oostenveld et al., 2011). Regardless of the online referencing, data will be re-referenced off-line to the average of both mastoids. Epochs will then be defined as +/- 600 ms around the target onset (or around the time when the target is expected to appear for no target trials). As in Mathewson et al., (2009), data will be resampled to 200 Hz, and ocular artifacts identified and corrected using the method described in Gratton et al. (1983). A semiautomatic artefact rejection procedure will be used to identify any signal deflection that exceeds +/- 250 μV as in Mathewson et al. (2009). Bad channels will be identified by visual inspection and interpolated. However, if the bad channels are the ones critical for the analysis (i.e., Fz and/or Pz), the entire dataset will be excluded from the analysis and replaced with a new one.

Power and phase estimation: The time of interest will be the -200 to 0 ms (relative to stimulus presentation) of target-mask trials for studies 1 and 2. As in Mathewson et al. (2009), for each subject and trial, a discrete Fourier Transform (no taper) will be applied to the EEG signal of electrode Pz and the phase and power will be extracted at a frequency of 10 Hz. Although in Study 2, there is scope to explore a wider parameter space, we decided to limit the registered analysis (and comparisons) to the same parameters as in Mathewson et al. (2009). This way, we can capitalize on Mathewson's et al. (2009) data for the sample size calculation in Study 2 and directly compare the two studies. Please note, however, that Study 2 will be run only if positive or inconclusive results from Study 1 are obtained.

Effects of oscillatory activity on detection rate (Hp a.1, Study 1 and 2): For each subject, trials will be divided into high and low power based on the median of log-transformed power. Additionally, high-power trials will be divided into two non-overlapping phase bins, each encompassing 180 degrees. As in Mathewson et al. (2009), the phase bin limits will be selected to be orthogonal to the mean phase of the miss trials.

For high-power trials, a paired t-test ($p < 0.02$, one tail) will be performed comparing the hit rate between "good" and "bad" phase bins. If visual perception operates in cycles, then this difference is expected to be significant (Hp a.1, Table 1). If this effect is significant for Study 1, but not for Study 2, or it is significant for both studies but larger for Study 1 (here and below tested by means

of a meta-regression, see Meta-Analysis section for details), then we should conclude that pre-target temporal jitter plays a key role in the relevance of the oscillatory phase for visual perception (Hp b.1, Table 1).

Phase opposition (Hp a.2,* S*tudy 1 and 2): To assess that alpha phases for hit and miss trials at the electrode Pz are concentrated around different phase values, as in Mathewson et al. (2009), phases will be converted into cartesian coordinates (i.e., two-dimensional unitarian vectors) by the following steps. For all calculations, we will express phases as complex numbers z:

$$z = e^{i\phi}, |z| = 1 \qquad \text{(Eq. 1)}$$

Where ϕ is the phase at a given trial. For each participant and trial outcome, mean vectors will be calculated ($\underline{z}_{Hit}$ and $\underline{z}_{Miss}$), reflecting information about the preferred direction and the concentration (the larger the concentration, the larger the magnitude of the mean vectors). Then, the mean vectors will be averaged across participants. Notice that the contribution of each participant to the group mean will be weighted by the concentration (i.e., participants showing a phase distribution concentrated around a preferred value will have a larger concentration and weight more than the grand average). Subsequently, grand average hit ($\hat{Z}_{Hit}$) and miss ($\hat{Z}_{Miss}$) phase direction will be calculated:

$$\hat{Z}_{Hit} = \frac{<\underline{z}_{Hit}>}{|<\underline{z}_{Hit}>|} \text{ (Eq 4)}$$

and a Hotelling paired bivariate test will be used to test if the difference between the grand average directions ($\Delta\hat{Z} = \hat{Z}_{Hit} - \hat{Z}_{Miss}$) significantly deviates from 0. To do that, first, the T squared statistic is obtained as follows:

$$T^2 = n\left(\Delta\hat{Z} - \mu_0\right)^T S^{-1}\left(\Delta\hat{Z} - \mu_0\right) \text{ (Eq 5)}$$

Where $\mu_0 = [0\ 0]$ is the direction corresponding to the null hypothesis and S^{-1} is the inverse of the sample covariance matrix. The elements in the covariance matrix are the differences between the grand average directions for hit and miss trials for each participant:

$$\Delta\hat{z} = \frac{\underline{z}_{Hit}}{|\underline{z}_{Hit}|} - \frac{\underline{z}_{Miss}}{|\underline{z}_{Miss}|} \text{ (Eq 6)}$$

Finally, F value is obtained from the T-squared statistic:

$$F_{p,n-p} = \frac{n-p}{(n-1)p} T^2 \text{ (Eq 7)}$$

where the degrees of freedom are obtained from the number of participants (n) and the number of variables (p=2, the number of elements of the vector). From the F value, a p-value will be obtained. We will consider that the phase difference between hit and miss trials differs significantly from zero if the p-value is below 0.02 (alpha level = 0.02). According to Hp a.2 (Table 1), in both Studies 1 and 2, we expect that the phase for hit and miss trials will be concentrated into different (opposite) angles. In the case this effect is significant for Study 1 but not for Study 2, or significantly larger in Study 1, then we should acknowledge the role of temporal expectations in the perceptual cycle hypothesis (Hp b.1, Table 1; Table 2).

N1 amplitude and latency effect (Hp a.3,* S*tudy 1 and 2)

As described in Mathewson et al. (2009), target-only trials will be used to test the phase effect on the N1 event-related component. Trials will be sorted according to the 10 Hz phase at target onset using the same bins defined for Hp a.1. ERPs time-locked to the target will be calculated for each bin and baseline corrected to the 200 ms preceding the stimulus onset. Finally, the peak amplitude and associated latency will be measured for the electrode Fz in the time window between 50 and 170 ms post-target onset for each participant and bin. Note that this window was used to replicate Barry et al. (2004) in the original study (Mathewson et al., 2009). Two separate one-tailed t-tests will be performed to test for significant differences between "good" and "bad" phase bins in N1 amplitude and latency. If N1 amplitude and/or latency are different between phase bins, it will be electrophysiological evidence for the rhythmicity in visual processing (Hp a.3, Table 1). If this effect is significant for Study 1, but not for Study 2, or it is larger in Study 1 compared to Study 2, then we should conclude that temporal expectations affect visual processing (Hp b.1, Table 1; Table 2). The impact of the number of labs will be taken into account by directly comparing only data from labs participating in both experiments.

Quality Checks

Before data collection, each lab will provide evidence of timing accuracy in their setting using a photodiode/oscilloscope. Furthermore, to ensure the quality of each dataset, we have set in place some quality checks. First, only the datasets (from any replicating lab) whose signal-to-noise ratio (SNR) at the grand average N1 component (latency 150-230 ms after target onset, electrodes Fz, N=35 participants) from the target-only trials larger than 0 dB will be considered for the analysis. This quality check must be accomplished for both Studies 1 and 2. We will consider that the replication attempt failed if less than 3 out of the N replicating labs do not fulfil this quality check for Study 1 (Pavlov et al., 2021).

Furthermore, only for Study 2, where stimulus onset will be jittered, we expect that phases at target onset will be randomly distributed when sorted irrespective of the behavioural outcome. This will be tested through a Rayleigh test (Berens, 2009) for each participant and lab. For each replicating lab, the resulting p-values will be combined using a conservative method (Friston's method, Friston et al., 1999). If the lab-combined p-value is above 0.02, the data of the replicating lab will be considered to fulfil the phase randomness at the onset quality check.

Meta-Analysis

For each hypothesis separately, we will, first, compute effect sizes (Cohen's d) for each individual lab and then combine all datasets in a random-effects meta-analysis (with labs as a random effect) using the REML estimator for random-effects variance. We will report and plot the median and distribution of the weighted effect sizes, their 95% confidence intervals, heterogeneity (τ^2), and the number of labs successfully replicating the original effect. The metafor package (Viechtbauer, 2010) for R will be used for the meta-analyses.

We will use JASP or the equivalent BayesFactor package in R to conduct corresponding Bayes factor (BF) analyses for each frequentist test. These BF analyses will be particularly informative in cases where the frequentist test is not significant. In addition, a random-effects Bayesian meta-analysis (Love et al., 2019) will be used to complement the random-effects meta-analysis. Bayes factors larger than 6 (or smaller than 1/6) will be considered evidence for (or against) an effect. BF between 6 and 1/6 will be considered as inconclusive. Importantly, the decision whether to run experiment 2 (see Table 2), will depend on the Bayesian meta-analysis. Thus, study 2 will only be run if the meta-analytic BF provides positive evidence or remains inconclusive (i.e. is

greater than 1/6). We will use default priors from JASP for all BF analyses (Cauchy prior with a scale of 0.707).If Study 2 is run, we will compare effect sizes in a frequentist version of random-effects meta-regression.

Data and Code sharing

The experimental code, the code for analysis and the data (BIDS format) will be populated in our Open Science Framework Repository: https://osf.io/mtv8r/.

Figures and Tables

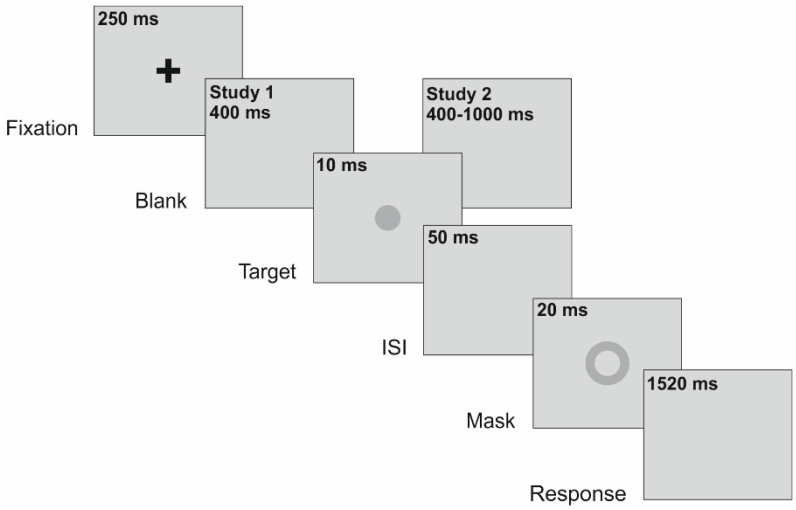

Figure 1. Schematic representation of a trial in Study 1 and 2. Please note that events' timings are specific to a 100 Hz monitor.

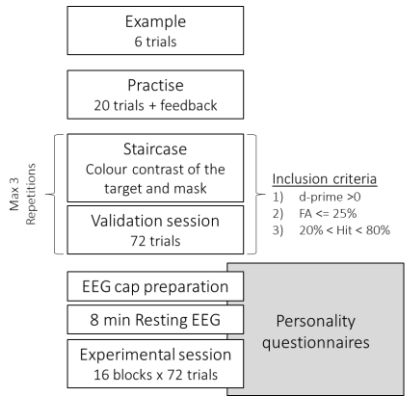

Figure 2. Procedure followed by each Replicating Lab. The grey area indicates when Personality questionnaires will be administered, i.e., from before the EEG cap preparation to the end of the experiment. This info will be noted by each Lab.

Table 1. Summary of the hypotheses tested in Studies 1 and 2, including the tests and results from Mathewson et al. (2009), sample size estimations, and tests in the current RR.

Replication - Hp a.1 *Effects of oscillatory activity on detection rate* **estimated sample size = 27** When low-frequency power is high, oscillatory phase influences perception	
Test in Mathewson et al., (2009)	Paired t-test (2-tail) comparing the detection rate in the two pre-selected phase bins (225– 45° and 45–225°) in trials with high alpha power only (t(10)= 4.53, p=0.005), which corresponds to a Cohen dz = 1.366

Tests **Studies 1 and 2**	Paired t-test (1-tail, $p<0.02$) comparing the detection rate in the two pre-selected phase bins (as much as orthogonal as possible to the miss/hit phase mean) in trials with high alpha power only.
Replication - Hp a.2, *Phase Opposition* **estimated sample size = 20** Low-frequency oscillations modulate the probability of perceiving a target within one oscillatory cycle: detection rate is associated with separated (ideally, opposite) phase angles	
Test in Mathewson et al., (2009)	For hit and miss trials, the resultant X and Y Cartesian components of phase were submitted to a Hotelling's bivariate F test for a difference from zero ($F(2,9)= 22.00$, $p<0.001$), which corresponds to a Cohen dz = 2.108
Tests **Studies 1 and 2**	For hit and miss trials, the resultant X and Y Cartesian components of phase will be submitted to a Hotelling's bivariate F test for a difference from zero ($p<0.02$).
Replication - Hp a.3, *N1 amplitude and/or latency dependent on phase* **estimated sample size = 35 for N1 amplitude, =12 for N1 latency** Low-frequency phase at the onset of the stimulus has an impact on electrophysiological correlates of stimulus processing (e.g., N1 amplitude and/or latency)	
Test in Mathewson et al., (2009)	In the time window between 50 and 170 ms after target onset, there was a significant difference between miss (45 and 225°) vs hit (225 and 45°) phases in N1 amplitude (means =- 0.14 V vs -1.42 μV, $t(10)=3.89$, $p< 0.005$, 2-tail) and N1 latency (means = 100 ms vs 66 ms, $t(10)= 7.21$, $p< 0.0001$, 2-tail). N1 amplitude/latency Cohen's dz=1.173/; 2.174
Tests **Studies 1 and 2**	Two separate one-tailed t-tests ($p<0.02$) will be performed to test for significant differences between "good" and "bad" phase bins in N1 amplitude and latency.
Original - Hp b.1, *Spontaneous vs Temporal expectation effect* Behavioural and/or physiological low-frequency phase effects occur in the absence of temporal expectation	
Tests **Study 1 vs 2**	The effect sizes will be compared using mixed-effects meta-regression with study as a moderator

Table 2. Core predictions and possible outcome from Studies 1 and 2 and consequent interpretation of the results.

Legend: A red colour indicates a *No effect*, i.e., there is a significant meta-analytic estimate ($p>0.02$, $BF<1/6$) across labs for the effect to be against the core prediction; a green colour indicates a *Positive effect*, i.e., there is a significant meta-analytic estimate ($p<0.02$) across labs for the effect to be in favour of the core prediction; and yellow-colour indicates an *Inconclusive effect*; i.e., there is no evidence in favour or against the core prediction ($1/6 < BF < 6$ in the Bayesian random-effects meta-analysis).

The pre-stimulus oscillatory phase influences perception (at least when alpha power is high, and at least in one of the dependent variables tested, namely hit rate (Hp a.1), phase opposition (Hp a.2), N1 component within the studied parameters (Hp a.3)

Study 1 - fixed pre-stimulus interval, Mathewson et al. (2009) replication	**Study 2** - jittered pre-stimulus interval	**Interpretation** using the selected experimental design and analyses parameters
No effect	Study 2 will not be run	Oscillatory phase plays no role for subsequent perceptual responses
Positive effect	No effect	Temporal expectation influences the oscillatory phase, therefore, perception. However, the influence of the oscillatory phase on perception is not evident when temporal expectation is strongly minimized.
	Positive effect	Oscillatory phase plays a role for subsequent perceptual responses; see also Hp b.1.
	Inconclusive effect	Temporal expectation influences the oscillatory phase and, therefore perception. The effect of spontaneous oscillatory phase on perception is still unclear.
Inconclusive effect	No effect	The role of the oscillatory phase for subsequent perceptual responses is still an open issue, but only when temporal expectation is strongly involved; otherwise, the oscillatory phase plays no role for subsequent perceptual responses.
	Positive effect	The role of the oscillatory phase for subsequent perceptual responses is still an open issue, but only when temporal expectation is involved. On the contrary, the oscillatory phase influences subsequent

		perceptual responses when no temporal expectation is involved.
	Inconclusive effect	The role of the oscillatory phase for subsequent perceptual responses is still an open issue

Table 3. List of the replicating Labs and related setting info

Lab #	**Replicating Lab**	**Agreed to collect data for Study 2**	**Monitor type, refresh rate**	**Amplifiers**	**N. of encephalic electrodes**
1	Basque Center on Cognition Brain and Language (BCBL), Donostia/San Sebastian, ES	Yes	LCD, 100Hz	BrainProducts, BrainAmp DC	59
2	University of Nevada, Las Vegas, Las Vegas, NV, USA	Maybe	LCD, 100Hz	Biosemi Active 2	72
3	School of Psychology, University of Nottingham. Nottingham, UK.	Yes	LCD, 100Hz	Biosemi Active 2	64
4	Psychology, University of Dundee, Dundee, UK	Maybe	CRT, 85Hz	Biosemi Active 2	32
5	Department of Clinical and Experimental Sciences, University of Brescia, Brescia, Italy	Yes	LCD, 100Hz	BrainProducts, BrainAmp	32
6	Queensland Brain Institute, The University of	Yes	LCD, 100Hz	Biosemi Active 2	64

	Queensland, Queensland, MA, Australia				
7	Department of Cognitive Science, Indian Institute of Technology, Kanpur, India	Maybe	LCD, 100Hz	BrainProducts, ActiCHamp Plus	64
8	Research School of Psychology, Australian National University, Canberra, Australia	Maybe	LCD, 100Hz	Biosemi Active 2	64
9	Center for Mind/Brain Sciences (CIMeC), University of Trento, Italy	Maybe	LCD, 100Hz	Brain Products Brain Amp	32

Research question	**Hypotheses**	**Sampling plan**	**Analysis plan**	**Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis**	**Interpretation given different outcomes**	**Theory that could be shown wrong by the outcomes**
Does the alpha phase influence perception	Replication - Hp a.1 Effects of oscillatory activity on detection rate When low-frequency power is high, oscillatory phase influences perception. STUDY 1	N = 35	Paired t-test (1-tail, $p<0.02$) comparing the detection rate in the two pre-selected phase bins (as much as orthogonal as possible to the miss/hit phase mean) in trials with high alpha power only.	Exact replication of Mathewson et al., 2009	No effect in Study 1 Study 2 will not be run // Oscillatory phase plays no role for subsequent perceptual responses	Oscillatory phase plays no role for subsequent perceptual responses
	Replication - Hp a.2, Phase Opposition Low-frequency oscillations modulate the probability of perceiving a target within one oscillatory cycle: detection rate is associated with separated (ideally, opposite) phase angles. STUDY 1	N = 35	For hit and miss trials, the resultant X and Y Cartesian components of phase will be submitted to a Hotelling's bivariate F test for a difference from zero ($p<0.05$).		Positive effect in Study 1 No effect in Study 2	Temporal expectation influences the oscillatory phase, therefore perception. However, the spontaneous oscillatory phase does not influence perception
					Positive effect in Study 1 Positive effect in Study 2	Oscillatory phase plays a role for subsequent perceptual responses; see also Hp b.1
					Positive effect in Study 1 Inconclusive effect in Study	Temporal expectation influences the oscillatory phase,

					2	therefore perception. The effect of spontaneous oscillatory phase for perception is still unclear
	Replication - Hp a.3, N1 amplitude and/or latency dependent on phase Low-frequency phase at the onset of the stimulus has an impact on electrophysiological correlates of stimulus processing (e.g., N1 amplitude and/or latency). STUDY 1	N = 35			Inconclusive effect in Study 1 No effect in Study 2	The role of the oscillatory phase for subsequent perceptual responses is still an open issue, but only when temporal expectation is involved; otherwise, the oscillatory phase plays no role for subsequent perceptual responses
					Inconclusive effect in Study 1 Positive effect in Study 2	The role of the oscillatory phase for subsequent perceptual responses is still an open issue, but only when temporal expectation is involved. On the contrary, the oscillatory phase influences subsequent perceptual responses when no temporal expectation is involved.

					Inconclusive effect in Study 1 Inconclusive effect in Study 2	The role of the oscillatory phase for subsequent perceptual responses is still an open issue
	Original - Hp b.1, Spontaneous vs Temporal expectation effect Behavioural and/or physiological low-frequency phase effects occur in the absence of temporal expectation STUDY 2	Same as for each test in Study 1	Same as for each test in Study 1	Two separate one-tailed t-tests ($p<0.05$) will be performed to test for significant differences between "good" and "bad" phase bins in N1 amplitude and latency.		

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