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Research Report

Frequency-tagging as a measure of conscious face perception

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ABSTRACT

Steady-state visual evoked potentials (SSVEPs) from frequency-tagging (FT) paradigms are widely used to investigate visual processing. Yet their association to conscious perception remains unclear. To test whether SSVEP occurs during conscious perception or without consciousness, 32 participants saw sequences of different images presented at 6 Hz (6 images per second) and containing faces every fifth image (1.2 Hz). All images were presented at either 1% contrast or 1.5% contrast. After each sequence, participants had to categorise the face gender (objective perception) and rate their confidence in this categorisation and the visibility of the faces (subjective perception). During the sequence presentation, participants' attention was monitored via an orthogonal fixation-cross task. Results showed that, at 1.5% contrast, the face signal was higher during correct than during incorrect gender categorisation and increased linearly with both visibility and confidence ratings. In line with participants' performance on the fixation-cross task, the signal collected at 6 Hz also indicated that attention related more closely to confidence than to visibility. At 1% contrast however, no face perception occurred behaviourally, which was confirmed by the absence of brain signal recorded in response to face instances. Overall these findings show that SSVEPs can track both the objective and subjective perception of faces at a conscious contrast (1.5%). These findings bring new evidence that SSVEPs can be used as a marker of conscious perception.

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1. Introduction

Frequency-tagging (FT) involves the periodic presentation of a stimulus at a specific frequency (e.g., 6 Hz) while the neural activity is recorded at the scalp level of participants using electroencephalography (EEG; Morgan et al., 1996). When used to capture human visual aptitudes, this technique is known to elicit steady state visual evoked potentials (SSVEPs) that are visible over posterior brain regions at that specific frequency (e.g., 6 Hz). Over the years, SSVEPs have become increasingly popular as a tool to investigate the neural correlates of visual perception (Norcia et al., 2015; Vialatte et al., 2010), with

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disagreement about whether they can be used to mirror what is known as the 'true' correlates of consciousness (i.e., the neural correlates of consciousness that are distinct from prerequisites such as attention or post-perceptual processes such as introspection; Tsuchiya et al., 2015) or whether they should rather be considered as markers of attention (Davidson et al., 2020). To answer this question, we focused on a specific type of FT paradigm in which faces are introduced in streams of stimuli presented at a periodic rate (de Heering & Rossion, 2015; Heinrich et al., 2009; Jacques et al., 2016; Liu-Shuang et al., 2014; Quek & de Heering, 2024; Quek & Rossion, 2017; Retter & Rossion, 2016, 2017; Rossion et al., 2015) and, for the first time, in combination with behavioural reports for each sequence of stimuli. To put it differently, our main goal here was to investigate whether the SSVEPs associated with faces emerging periodically from other non-face stimuli can be used as a marker of conscious perception.

Traditionally, FT paradigms involve flickering stimuli that have been considered by some as markers of conscious perception, in particular when they are associated with binocular rivalry (Brown & Norcia, 1997; Jamison et al., 2015; Laukkonen et al., 2024; Zhang et al., 2011). To clarify, in binocular rivalry paradigms, each eye is presented with a different stimulus, which leads to the impossibility to fuse the two images in a single percept. As a result, participants' subjective experience of the stimuli is that of the abrupt alternations between the complete perception of one and then, of the other stimulus (Tong et al., 2006). Interestingly, when these stimuli flicker at two distinct frequencies, the consciously perceived stimulus is associated at a specific point in time (defined using behavioural reports) with higher SSVEPs responses at its stimulation frequency compared to the stimulation frequencies associated with the other stimuli, which indicates that SSVEPs can be taken as markers of consciousness (Brown & Norcia, 1997; Jamison et al., 2015; Laukkonen et al., 2024; Zhang et al., 2011). However, Davidson et al. (2020) recently challenged this view by demonstrating that SSVEPs are observed even when a visual stimulus remains physically present but is not consciously perceived. In that study, the authors used a perceptual filling-in paradigm and observed that, instead of a drop in the signal, the SSVEPs recorded were rather tracking the neural activity associated with the disappearing stimulus, with a significant increase of the brain response observed during the subjective disappearance of the stimulus. The authors concluded that, in this paradigm, SSVEPs track attention rather than conscious perception (Davidson et al., 2020), which also aligns with other findings taken from outside the field of consciousness (Andersen et al., 2008, 2011; Müller et al., 1998, 2006; Müller & Hillyard, 2000; Walter et al., 2012).

More recently, other FT paradigms have been developed to investigate higher-level visual processes such as visual categorisation (Jacques et al., 2016; Liu-Shuang et al., 2014; Retter & Rossion, 2016, 2017; Rossion et al., 2015). In these paradigms, participants are not only presented with sequences of different images presented at a fixed rate (e.g., 6 images per second; 6 Hz) but different instances of the same stimulus category (e.g., faces) are also embedded in these sequences at another, often slower, frequency (e.g., every 5th item and thus at 1.2 Hz). The rationale behind this paradigm is that if the brain is able to abstract a visual category from these periodic instances and to differentiate them from the other categories, SSVEPs will be observed (here at 1.2 Hz). In contrast, if no categorisation occurs, the brain will only produce SSVEPs at the image frequency (e.g., 6 Hz), signing for its general synchronisation to a set of images presented in a periodic fashion. Previous studies have relied on this paradigm to study not only face categorisation (Jacques et al., 2016; Liu-Shuang et al., 2014; Retter & Rossion, 2016, 2017; Rossion et al., 2015) but also the categorisation of other stimuli such as bird or houses (Quek & de Heering, 2024). However, to date, none of these studies have investigated directly whether SSVEPs collected in response to faces reflect their conscious perception or whether significant SSVEPs can also occur in the absence of consciousness. The only studies that collected behavioural reports that are necessary for this, and which relied on similar FT paradigms, have only done so indirectly by asking participants to report about the stimuli in a separate experiment (Bourgaux et al., 2025; Rekow et al., 2022; Retter et al., 2020). These studies indicated that participants who were aware, hence conscious, of the stimuli of interest presented in the sequence (e.g., faces in Retter et al., 2020; face pareidolia in Rekow et al., 2022) showed higher SSVEP amplitudes compared to participants who remained unaware of them. However, because in these studies data collection is performed outside of the stimulation sequences, this finding falls prey to the "retrospective assessment" criterion, which requires that subjective reports (e.g., about the visibility of the stimulus) is collected as close in time as possible to the objective measures (Stockart et al., 2025). In addition, there is large variability in the subjective responses collected from participants about how they perceive and judge the conscious content. Thus, within-subject manipulation of consciousness (i.e., having trials that participants are conscious about as well as trials that they are not conscious about within the same experimental design) is preferable to evaluate conscious perception. However, to our knowledge, such an approach does not exist currently in the field.

Here, we developed a within-subject design together with an FT paradigm where faces are introduced periodically within streams of other non-face images. All the stimuli presented in these streams were also degraded to two distinct low contrasts (1% and 1.5%). Specifically, we asked participants to perform an objective gender-face categorisation task on these degraded stimuli since we know this type of categorisation is automatic and can be performed in the near absence of top–down attention (Matthews et al., 2018). Participants had also to report their level of confidence in this categorisation as well as the visibility of the faces included in the stimulation sequences via the Perceptual Awareness Scale (PAS; Sandberg et al., 2010). Finally, participants performed an orthogonal task on the color-change of a fixation cross during each stimulation sequence to assess, and control for, the potential differences in attention across sequences and minimise the potential confounds from the post-perceptual processes.

We expected that if SSVEPs reflect conscious perception, the strength of the face-selective SSVEP response (at 1.2 Hz) would differ according to participants' behavioural reports for both measures of objective (i.e., higher for correct than incorrect responses to categorise gender) and subjective perception (i.e., higher for higher levels of visibility and confidence). In line with the idea that SSVEPs at the image frequency (6 Hz) reflect participants' dedicated attention to the stimuli (Liu-Shuang et al., 2014; Norcia et al., 2015), we also expected that this component would be less sensitive to subjective reports than the face-selective SSVEPs collected at 1.2 Hz, as we controlled for attention during sequence presentation with an attentional task.

2. Methods

2.1. Participants

We tested 32 participants based on Laukkonen et al. (2024), taking the confidence interval lower bound of a correlation between SSVEPs and behavioural responses (r = .81), an alpha at .05, and a power at 99%. These participants (22 females, mean age = 23.22, sd age = 5.36) were recruited at the Université libre de Bruxelles (ULB), Belgium, and awarded with course credits. We had the following inclusion/exclusion criteria: between 18 and 30 years of age, no history of epilepsy vision problems, or diagnosis of psychiatric/neurological conditions. Additionally, all participants reported normal or corrected-to-normal visual acuity. The Research Ethics Board of the department of Psychology of the Université libre de Bruxelles (Belgium) approved all experimental protocols (Reference–P2017/530/B406201734083).

2.2. Stimuli

We used a previously described set of 200 × 200-pixel coloured images (de Heering & Rossion, 2015; Jacques et al., 2016; Rossion et al., 2015) that contains 48 face images and 248 non-face images (e.g., animals, houses, fruits, vegetables, flowers, plants, objects). Face images varied in terms of colour composition, age, sex, viewpoint, lighting conditions, and were unsegmented from the background (see Fig. 1 for examples of both face and non-face images). We then equalised the contrast and mean pixel luminance of all images to avoid difference in low-level properties using Adobe Photoshop CS6 and ran a pilot study (see Supplementary Results) in which we estimated the between-subject variability in face-gender categorisation threshold contrasts across a sample of 19 participants. From this study, we concluded that the highest contrast for which participants accurately categorise the gender of the faces in 50% of the trials at an individual level is located at 1% of contrast and is consistent across participants (i.e., the same for 88% of the sample we tested). Given our goal of testing whether SSVEPs can reflect conscious perception of the flickering stimulus and/or if they rather reflect unconscious brain activity, we used, for the current study, two distinct and fixed contrasts: a 1% contrast and the adjacent higher contrast to participants' threshold contrast observed in the pilot study (i.e., 1.5%).

2.3. Procedure

Participants sat 1 m away from an LCD computer screen (resolution of 1280 × 1024 refresh rate of 60 Hz) where images were centrally presented at 6.7 × 6.7 degrees of visual angle. They were exposed to sequences of various stimuli presented at the frequency of 6 Hz (i.e., 6 images per second) meaning that each image appeared on the screen for 83.33 msec and was followed by a blank interval of 83.33 msec, for an image cycle duration of 166.66 msec (square-wave stimulation). Participants saw 60 sequences presented randomly (30 per contrast level). Within each sequence, a face image was embedded every 5th image and consequently presented at 1.2 Hz (6 Hz/5). The rest of the stimuli were non-face stimuli. Each sequence was also composed of a 1.67-sec fade-in period, a 40-sec period of interest (48 faces and 192 non-faces for a total of 240 images) and a 1.67-sec fade-out period. During the fade-in and fade-out, the maximal contrast of the images progressively ramped up or down to either 1% or 1.5% according to the sequence to minimise the artefacts elicited by the sudden appearance or disappearance of the stimuli.

Each sequence started with a "ready?" message, and participants were instructed to press the spacebar to initiate the sequence. Then, a central black fixation-cross appeared for between 1 and 5 sec, after which the stimulation sequence started. During the entire sequence, the fixation-cross remained superimposed on the images. Participants were instructed to fixate the cross and press the spacebar when it turned blue. Importantly, these changes occurred non-periodically. As used in previous studies (Jacques et al., 2016; Liu-Shuang et al., 2014; Quek & de Heering, 2024; Quek & Rossion, 2017; Rossion et al., 2015), this orthogonal task allowed to control the level of attention participants gave to the images across the sequences.

At the end of each sequence, participants had to: (a) give a subjective rating of the visibility of the faces they saw during the sequence using the Perceptual Awareness Scale (PAS; Ramsøy & Skov, 2010; Sandberg et al., 2010); (b) decide whether the faces corresponded to a male or a female face; (c) give their level of confidence in their gender decision. The PAS was a 4-point scale where each point corresponds to: (1) no impression of the stimulus (no experience), (2) a feeling that something has been shown, with a content that cannot be specified any further (brief glimpse), (3) an ambiguous experience of the stimulus, with some aspects being experienced more vividly than others and a feeling of almost being certain of it (almost clear experience), or (4) a non-ambiguous experience of the stimulus with no doubt about its own answer (clear experience). Accordingly, the confidence scale was spread over 4 levels of confidence ranging from 1 (guessing) to 4 (perfectly confident).

The entire procedure is summarised in Fig. 1. The task was programmed in Python using the Expyriment package (code available at https://github.com/amazancieux/freq_tag_consciousness/tree/main/FreqTagStim).

2.4. EEG recordings and preprocessing

During the entire task, we recorded participants' scalp EEG using a 64-channel Biosemi ActiveTwo system (Biosemi, Amsterdam, Netherlands). The EEG analog signal was digitised at a 1024 Hz sampling rate. Preprocessing of EEG data was performed using custom python scripts with the mne module (Gramfort et al., 2013) and functions of the PREP pipeline (Bigdely-Shamlo et al., 2015). We also identified bad channels using the random sample consensus (RANSAC)

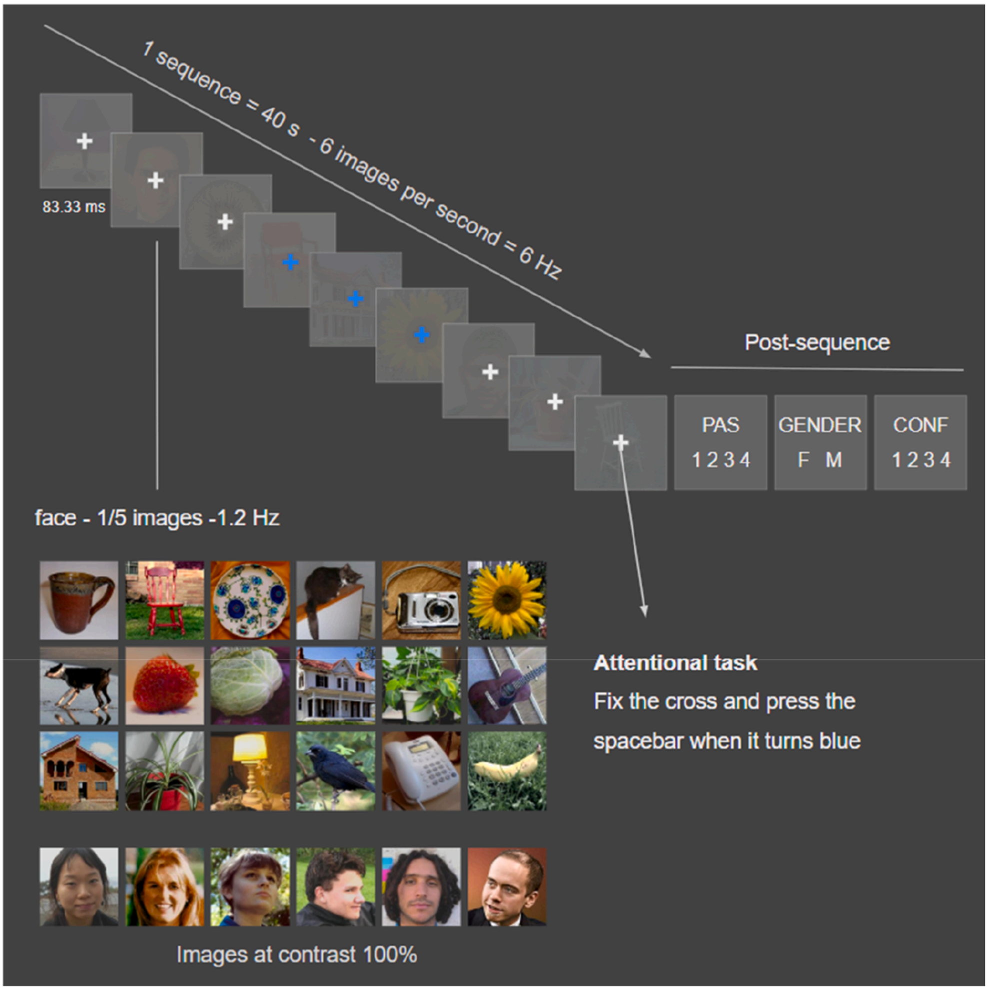

Fig. 1 – Stimuli and procedure. During a frequency-tagging (FT) sequence, stimuli were presented at 1% contrast or 1.5% contrast. Each sequence contained 240 images and lasted for 40 sec (excluding the fade-in and the fade-out period). At the end of the sequence, participants had to evaluate a) the visibility of the face using the PAS (Perceptual Awareness Scale), b) the gender of the face (female or male; GENDER) and c) rate their confidence (CONF) in their gender decision. During the entire sequence, participants also performed a concurrent color-change fixation-cross task with the goal of monitoring their attention.

method which predicts the EEG signal for each channel from the neighbouring channels. If the predictions failed to meet a threshold, the channel was identified as bad (mean number of bad channels = 6.59, sd = 3.23) and was spherically interpolated. We then applied a band-pass filter (.1–100 Hz) and downsampled the data to 250 Hz. To detect eye movements (blinks and saccades), we used the find_bad_eog function in MNE-Python (Gramfort et al., 2013), which correlates independent components with electrodes labelled as EOG (i.e. electrooculography). We used as EOG the Fp1 and Fp2 electrodes as they were the closest electrodes from the eyes. Independent components with a correlation higher than .5 were also removed from the data (mean = 1.38, SD = .60). The whole EEG data was then re-referenced to the average of all electrodes, and we finally segmented all epochs to 40-sec, hence excluding the fade-in and the fade-out period associated to each sequence.

To increase signal-to-noise ratio (SNR), we next averaged the epochs (Quek & de Heering, 2024; Rekow et al., 2020) according to participants' behavioural responses (i.e., their PAS scores (4 levels), whether face categorisation was correct or incorrect (2 levels), and their confidence level (4 levels), for each contrast (2 contrasts), leading to 8 conditions for the PAS ratings (4 PAS ratings × 2 contrasts), 4 conditions for the categorisation (correct/incorrect × 2 contrasts), and 8 conditions for confidence (4 confidence levels x 2 contrasts). For each condition, we finally computed the power spectrum of the signal using the Welsh method (frequency resolution = .025 Hz) and extracted the SNR using 10 neighbouring bins per side and skipping the 2 adjacent bins (Rossion et al., 2015) at the face frequency (1.2 Hz) and the image frequency (6 Hz). Our analyses focused on 3 region-of-interests (ROIs) defined a priori, based on Quek and de Heering (2024). For the investigation of a face response, we defined two occipito-temporal (OT) ROIs (Left OT: PO3, P7, PO7, P9, O1; Right OT: PO4, P8, PO8, P10, O2) which typically capture the brain responses associated with face categorisation (Hagen & Tanaka, 2019; Jacques et al., 2016; Quek & de Heering, 2024). For the general image response, we focused on an occipital ROI (O1, O2, Oz), as in previous studies (de Heering & Rossion, 2015; Jacques et al., 2016; Quek & de Heering, 2024; Rossion et al., 2015).

2.5. *Statistical analyses*

The statistical analyses performed on the behavioural data included linear models for the PAS ratings, gender-face categorisation, and the confidence ratings across the 2 contrasts (1% and 1.5%). We evaluated sensitivity to the gender of faces using *d* primes (d') from the signal detection theory (Swets & Green, 1978). We also calculated M-ratio (meta-d'/d') from the meta-d' framework (Fleming, 2017; Maniscalco & Lau, 2014) using confidence ratings, which is considered as an index of metacognitive efficiency (i.e., the ability to discriminate between correct and incorrect responses while controlling for the overall task performance). According to this measure, the closer M-ratio is to 1, the more optimal metacognitive efficiency is (see Maniscalco & Lau, 2014).

For the EEG analyses, we ran 3 linear mixed-effect models on the SNR extracted at the face frequency (1.2 Hz) and the SNR extracted at the image frequency (6 Hz). These models always included the following variables: contrast (1% and 1.5%), behavioural responses (either PAS ratings [from 1 to 4], gender categorisation accuracy [correct and incorrect], or confidence ratings [from 1 to 4]), and ROI (left OT and right OT for the face signal and the occipital ROI for the image signal). These models were computed with lmerTest package in *R* (Kuznetsova et al., 2017) and the number of parameters were estimated by fitting a Principal Components Analysis (PCA) of the random-effects variance-covariance estimates from a 'maximal' mixed-effects model including all possible random effect components except for the ROI random effect (Bates et al., 2015). For all 3 models, the number of estimated random effects are detailed in the Result section. Effect size (Cohen's d) were finally estimated from each *t* value.

For the orthogonal task that we used as a control of participants' allocated attention to the stimuli during the sequences, we compared their performance in detecting the color change of the fixation cross (percentage of correct detection based on the number of correct detections divided by the number of color changes in a sequence) across contrasts (2 levels) and behavioural responses (4 PA S levels; correct/incorrect responses; 4 confidence levels) using 2 mixed-effect models in a similar manner as for the abovementioned EEG analyses. Importantly, a detection was counted as correct when the participant pressed the spacebar within the timing of the fixation cross being blue.

All statistical analyses were performed using R. All task, preprocessing, and analysis scripts are available freely at https://github.com/amazancieux/freq_tag_consciousness. Behavioural and EEG data are also available at https://osf.io/7hkn6/files/osfstorage.

3. Results

3.1. *Behaviour for objective perception (categorisation) and subjective perception (visibility and confidence)*

We first compared participants' sensitivity (d') to categorize gender across contrast levels. As expected, d' was higher at 1.5% (mean = 2.57, sd = .94) than at 1% (mean = .51, sd = .66), t (31) = 4.90, $p < .001$, dz = .87. Sensitivity was also only significantly different from chance at 1.5% (t (31) = 7.92, $p < .001$, dz = 1.40) and not at 1% (t (31) = 1.73, $p = .092$, dz = .31).

We then compared participants' mean PAS and mean confidence ratings across accuracy at the gender categorisation task (correct, incorrect) and across the 2 contrasts (1%, 1.5%). We first observed that 10 out of the 32 participants tested did not show any incorrect responses at 1.5%. Their data were thus removed from this specific set of analyses. We then computed a linear model on the rest of the data (22 subjects) and found, for mean PAS, a main effect of accuracy, t (21) = 4.26, $p < .001$, dz = .90, a main effect of contrast, t (21) = 9.20, $p < .001$, dz = 1.96, and an interaction between the two factors, t (21) = 5.01, $p < .001$, dz = 1.06. When decomposing the interaction, we found no significant difference between correct (mean = 1.32, sd = .49) and incorrect (mean = 1.23, sd = .44, t (31) = 1.53, $p = .136$) responses at 1% of contrast but significantly higher mean PAS for correct (mean = 2.78, sd = .86) than incorrect responses (mean = 1.91, sd = .88, t (21) = 4.78, $p < .001$, dz = 1.02) at 1.5%, suggesting that participants rated visibility higher when they were correct compared to incorrect in the gender categorisation task at 1.5%, but not at 1% contrast (Fig. 2A).

For mean confidence, the pattern was the same: we found a main effect of accuracy, t (21) = 3.92, $p < .001$, dz = .84, a main effect of contrast, t (21) = 7.77, $p < .001$, dz = 1.66, and an interaction between the two factors, t (21) = 4.84, $p < .001$, dz = 1.03. In fact, there was no difference between correct (mean = 1.59, sd = .83) and incorrect responses (mean = 1.56, sd = .86, t (31) = 1.82, $p = .077$) at 1% contrast and mean confidence was also higher for correct (mean = 3.14, sd = .90) than incorrect responses (mean = 2.01, sd = .97, t (21) = 4.40, $p < .001$, dz = .93) at 1.5% contrast. As for PAS, this pattern suggests that participants knew when they were correct and incorrect in the gender categorisation task since they responded differently in terms of confidence, but only at 1.5% contrast (Fig. 2B). Turning to the M-ratio scores, participants obtained higher M-ratio at 1.5% (mean = .76, sd = .53) than at 1% (mean = −.31, sd = 1.02), t (31) = 4.90, $p < .001$, dz = .87, and their scores were only significantly different from zero at 1.5% contrast, t (31) = 7.92, $p < .001$, dz = 1.40, but not at 1% contrast, t (31) = −1.74, $p = .092$), suggesting again that participants discriminated between correct and incorrect responses but only at 1.5% contrast.

In summary, behavioural results showed that the categorisation task was performed better than chance at 1.5% contrast only, and hence gender discrimination was only possible at this contrast level. At the subjective level, dissociative patterns between correct and incorrect trials were

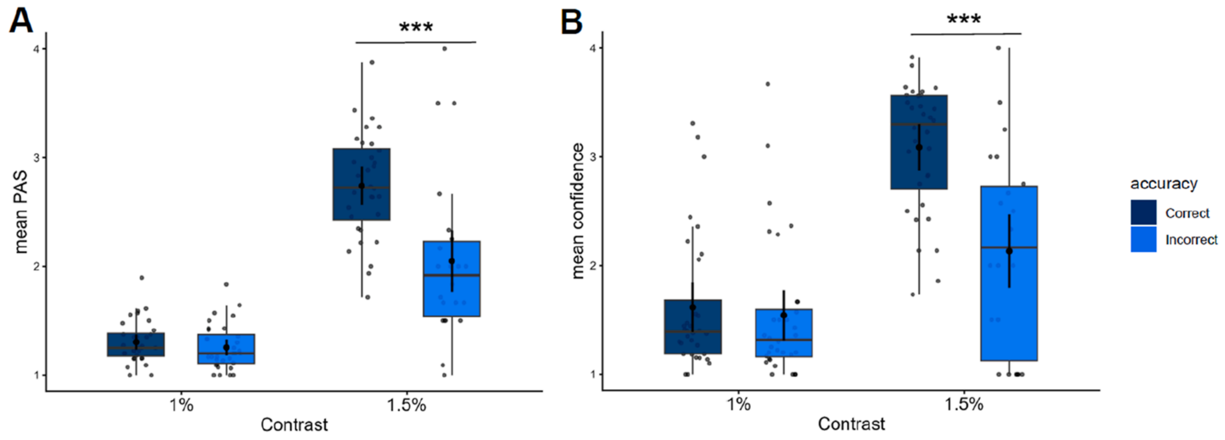

Fig. 2 – Behavioural responses. A) Mean PAS as a function of accuracy (correct *vs* incorrect) and contrast (1% *vs* 1.5%). B) Mean confidence as a function of accuracy (correct *vs* incorrect) and contrast (1% *vs* 1.5%). Error bars represent standard errors. Dots represent individual mean PAS per contrast and accuracy.

observed with higher face visibility and confidence ratings in the gender decision task. We also found an overall above chance metacognitive efficiency but only again, at 1.5%, suggesting that conscious perception was possible at 1.5% but not at 1%.

3.2. *Brain responses at the face frequency (1.2 Hz) for objective perception (face categorisation)*

We compared SNR at the face frequency (1.2 Hz) across the 2 contrasts (1% *vs* 1.5%), the gender categorisation accuracy (correct *vs* incorrect) and the 2 face ROIs (left OT *vs* right OT) using a linear mixed-effect model (Fig. 3A). The model included a random intercept and a slope for the accuracy effect for each participant. We found a main effect of contrast, t (185.20) = 5.90, $p < .001$, dz = 1.04, with higher SNR at 1.5% than at 1% contrast, and a main effect of accuracy, t (31.47) = 3.84, $p < .001$, dz = .68, with higher SNR for sequences associated with correct than incorrect responses. Additionally, we found a significant interaction between accuracy and contrast, t (185.20) = 3.51, $p < .001$, dz = .62, with no SNR difference between correct and incorrect responses at 1%, t (66.92) = .88, $p = .333$, but higher SNR for correct than incorrect responses at 1.5%, t (82.66) = 4.97, $p < .001$, dz = .88. No other effect was significant. These results suggest that the brain response at the face frequency (1.2 Hz) was higher during correct than incorrect gender categorisation, but only at 1.5% contrast.

3.3. *Brain responses at the image frequency (6 Hz) for objective perception (face categorisation)*

Next, we compared SNR at the image frequency (6 Hz) in the occipital ROI across the 2 contrasts (1% *vs* 1.5%) and across gender accuracy (correct *vs* incorrect) using another linear mixed-effect model (Fig. 3B). The model included a random intercept per participant. We found a main effect of accuracy, t (85.13) = 4.48, $p < .001$, dz = .79, where SNR was higher for correct than incorrect responses. We also found a significant interaction between contrast and accuracy, t (85.13) = 2.35, $p = .021$, dz = .42. Simple effects revealed no difference between correct and incorrect responses at 1% contrast, t (83.1) = 1.61, $p = .112$, and higher SNR for correct compared to incorrect response at 1.5% contrast, t (86.71) = 4.57, $p < .001$, dz = .81. No other effect was significant. These results suggest that the brain response for image frequency (6 Hz) was higher during correct than incorrect gender categorisation, but only at 1.5% contrast.

3.4. *Brain responses at the face frequency (1.2 Hz) for subjective perception (visibility and confidence)*

We now turn into the comparison of SNR at the face frequency (1.2 Hz) across the 2 contrasts (1% *vs* 1.5%), PAS or confidence ratings (from 1 to 4), and the 2 face ROIs (left OT *vs* right OT) using two distinct linear mixed-effect models. For the PAS ratings (Fig. 4A), the model included a random intercept and a slope for the effect of PAS for each participant. Results only indicated a significant interaction between PAS ratings and contrast, t (291.84) = 1.98, $p = .048$, dz = .35. Simple effects further showed no difference across PAS ratings at 1% contrast, $b = .02$, t (229.58) = .07, $p = .942$. Critically however, a significant and positive linear effect was found at 1.5% contrast, $b = .33$, t (44.73) = 3.65, $p < .001$, dz = .65.

For confidence ratings (Fig. 4B), the model only included a random intercept for each participant, the random slope for the confidence effect being too close to zero to be included in the model. Interestingly here, we found a main effect of confidence, t (351.95) = 3.11, $p = .002$, dz = .55, where SNR increased linearly with confidence across the 2 contrasts. There was also a significant interaction between confidence ratings and contrasts, t (351.95) = 3.86, $p < .001$, dz = .68. Additionally, there was no difference across confidence ratings at 1% contrast, $b = -.05$, t (358.62) = −.45, $p = .657$, but a significant and positive linear effect at 1.5% contrast, $b = .46$, t (354.89) = 5.55, $p < .001$, dz = .98.

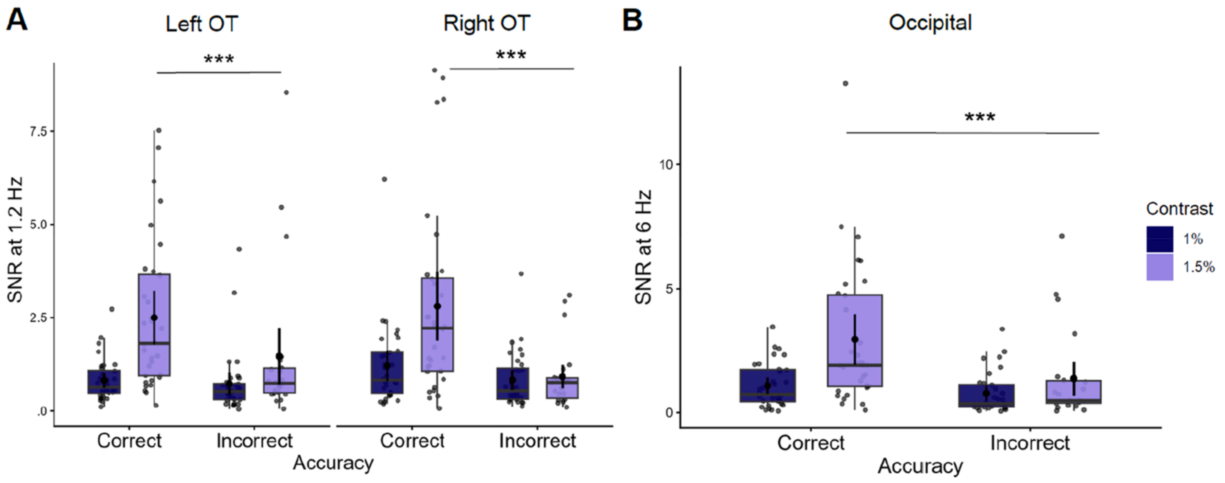

Fig. 3 – A) SNR at the face signal (1.2 Hz) according to accuracy (correct, incorrect) for each contrast (1%, 1.5%) and each face ROI (left OT, right OT). Error bars represent standard errors. B) SNR at the image signal (6 Hz) according to accuracy (correct, incorrect) for each contrast (1%, 1.5%) at the occipital ROI. Dots represent individual SNR per contrast and accuracy.

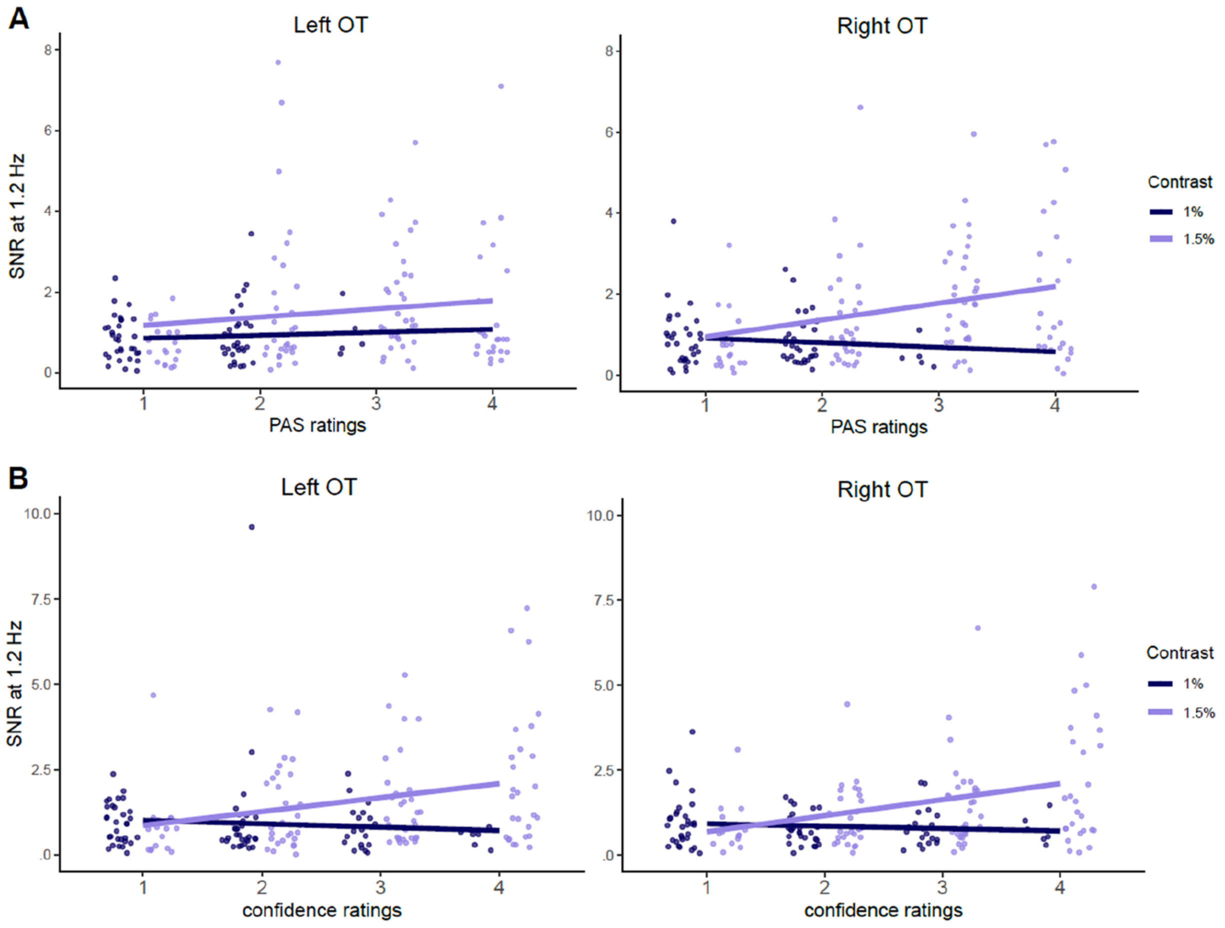

Fig. 4 – A) SNR at the face signal (1.2 Hz) according to PAS ratings (from 1 to 4) for each contrast (1%, 1.5%) and face ROI (left OT, right OT). B) SNR at the face signal (1.2 Hz) according to confidence ratings (from 1 to 4) for each contrast (1%, 1.5%) and face ROI (left OT, right OT). Dots represent individual SNR per PAS/confidence and contrast.

In summary, the pattern of result was similar for PAS and confidence at 1.5% contrast: brain responses at the face frequency (1.2 Hz) increased linearly with subjective ratings (visibility and confidence). No significant effect was observed at 1%. Corresponding topographies are presented in Fig. 6A.

3.5. *Brain responses at the image frequency (6 Hz) for subjective perception (visibility and confidence)*

Next, we compared SNR at the image frequency (6 Hz) at the occipital ROI across the 2 contrasts (1% *vs.* 1.5%) and across PAS or confidence ratings (from 1 to 4) using two distinct linear mixed-effect models. For PAS ratings (Fig. 5A), the model included a random intercept per participant and a random slope for the PAS effect. Results showed a significant interaction between PAS ratings and contrasts, t (109.89) = 3.59, $p < .001$, dz = .63. Simple effects further revealed a significant and negative effect of PAS ratings at 1% contrast, $b = -12.15$, t (137.58) = −3.04, $p = .003$, dz = .54, but no significant difference across PAS ratings at 1.5% contrast, $b = 3.02$, t (48.50) = 1.39, $p = .174$.

For confidence ratings (Fig. 5B), the model included a random intercept per participant. We found a significant interaction between confidence ratings and contrasts, t (159.26) = 4.79, $p < .001$, dz = .84, where, again, there was a significant and negative effect of confidence at 1% contrast, $b = -6.60$, t (162.18) = −3.11, $p = .002$, dz = .55, and a significant positive effect of confidence at 1.5% contrast, $b = 6.34$, t (160.59) = 3.70, $p < .001$, dz = .65.

Overall, these results suggest a similar pattern for PAS and confidence at 1% where brain responses linearly decrease as PAS ratings and confidence decreases. However at 1.5%, a linear increase in brain responses with confidence ratings was observed despite no difference across PAS ratings. Corresponding topographies are presented in Fig. 6B.

3.6. *Performance at the attentional task (colour-change fixation cross task)*

Turning to performance at the attentional task, we first observed a correct task compliance for both contrasts (for the 1% contrast: mean = .78, sd = .15; for the 1.5% contrast: mean = .75; sd = .16). Next, we analysed performance at the task using 3 distinct linear mixed-effect models to compare performance across contrasts and separately for each behavioural responses (either PAS ratings [from 1 to 4], gender discrimination accuracy [correct and incorrect], or confidence ratings [from 1 to 4]), exactly as what we did for brain responses. Each of the 3 models included a random intercept per participant. Note that due to technical issues, the data of 3 participants was not available for this task. For the 3 models, we found a main effect of contrast showing that task performance was higher at 1% than at 1.5% contrast (t (1513.57) = 3.24, $p = .001$, dz = .60 for the PAS model, t (1511.44) = 2.71, $p = .007$, dz = .50, the accuracy model, t (1515.95) = 4.54, $p < .001$, dz = .84, and the confidence model (t (1515.95) = 4.54, $p < .001$, dz = .55). This observation supports the idea that less attention was allocated to the orthogonal task at 1.5% contrast. For the confidence model, we also found an interaction between contrast and confidence, t (1517.71) = 3.21, $p = .001$, dz = .60, which was characterised by a significant and linear positive effect of confidence ratings at 1.5% contrast, t (1523.41) = 3.10, $p = .002$, dz = .58, but not at 1% contrast, t (1527.51) = 1.32, $p = .188$. These results suggest that performance at the detection task linearly increased with confidence 1.5% contrast only.

4. Discussion

In this study, we used a specific FT paradigm to test whether SSVEPs elicited at the category frequency (i.e., the face frequency) reflect the participants' conscious perception of faces or if they can also occur in the absence of consciousness (Bourgaux et al., 2025; Davidson et al., 2020; Rekow et al., 2022; Retter et al., 2020). To do so, we degraded all the stimuli to two contrast levels: a 1% contrast and a 1.5% contrast level. Crucially, at the end of each sequence, participants had to report about the faces presented in the sequences which allowed us to evaluate both their objective (gender-face categorisation) and subjective perception of the faces (visibility

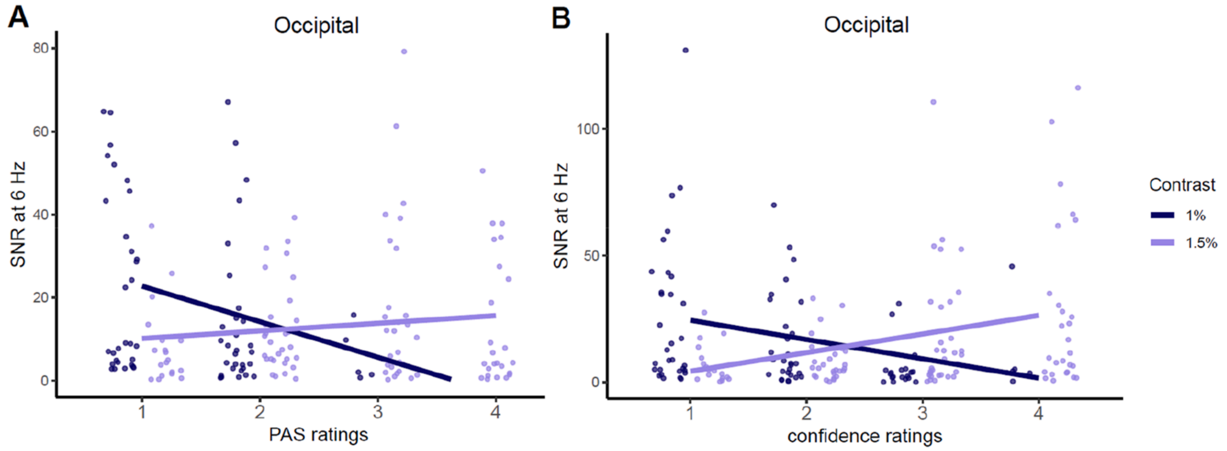

Fig. 5 – A) SNR at the image signal (6 Hz) according to PAS ratings (from 1 to 4) for each contrast (1%, 1.5%). B) SNR at the image signal (6 Hz) according to confidence ratings (from 1 to 4) for each contrast (1%, 1.5%). Dots represent individual SNR per PAS/confidence and contrast.

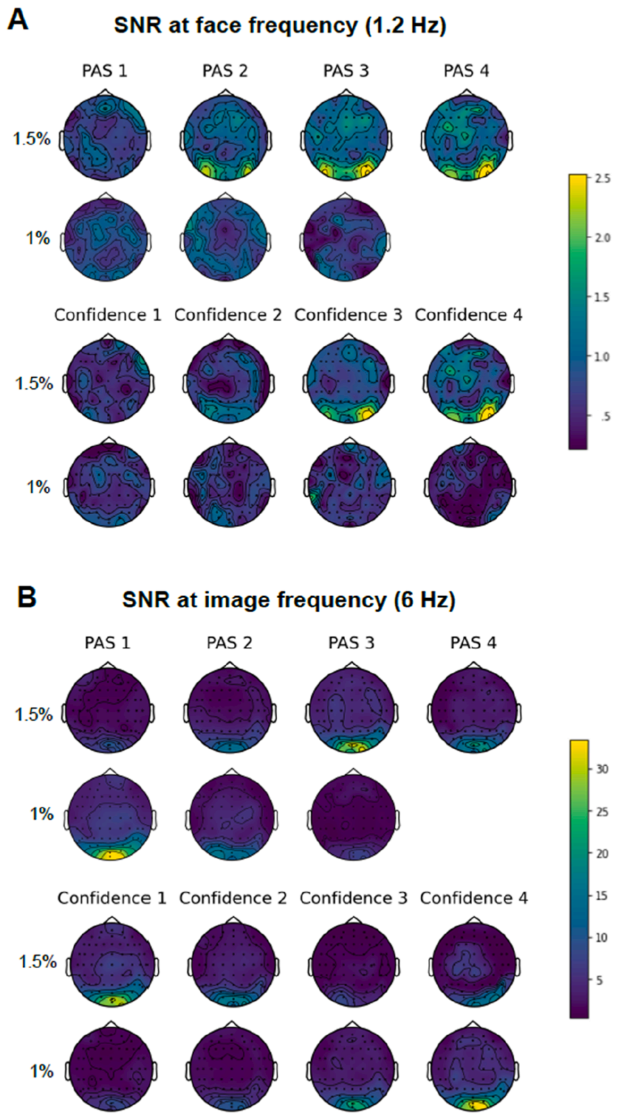

Fig. 6 – A) SNR topographies at the face signal (1.2 Hz) for each contrast (1%, 1.5%) according to PAS ratings (from 1 to 4) or confidence ratings (from 1 to 4). B) SNR topographies at the image signal (6 Hz) for each contrast (1%, 1.5%) according to PAS ratings (from 1 to 4) or confidence ratings (from 1 to 4).

and confidence) in order to test whether SSVEPs relate to conscious perception, or not.

The results revealed a distinct pattern according to the contrast of the images. First, at 1% contrast, participants were not able to categorise behaviourally the gender of the faces (objective d' were not significantly different from zero at the group level). We also did not observe any significant difference in subjective ratings across correct and incorrect responses for both visibility and confidence, nor was the metacognitive efficiency significantly different from zero at this contrast level. Consistently, participants' brain responses, indexed by their SNR at the face frequency, did not differ across behavioural responses (PAS ratings, gender categorisation accuracy, or confidence ratings). However, only limited conclusions can be drawn from this level of contrast because 1% could have been too low to elicit a significant brain response at the group but not at the individual level. Moreover, even if category tagging fails, some subthreshold structural encoding might also have occurred at this contrast level.

Conversely, at 1.5% contrast, the pattern was very different and clearer. First sensitivity to face gender was significantly different from zero, indicating objective perception at this contrast. Subjective perception was also marked by higher visibility and confidence ratings for correct compared to incorrect categorisation responses, as well as by metacognitive efficiency scores that were significantly above zero, suggesting that participants had metacognitive access to their categorisation performance at this contrast level. Moreover, at 1.5%, the SNR recorded at the face frequency varied with visibility and confidence, which indicates that across sequences of the same signal strength, variability in subjective perception can be observed and measured using SSVEPs. Interestingly from the topographies, it also seems that when participants reported not having seen the faces (PAS = 1), no SSVEPs occurred and it is only when participants experienced a brief glimpse (PAS = 2) and above (PAS = 3 or 4) that activity in the OT regions increased linearly. Thus, our FT paradigms captured graded differences in subjective perception which also suggests that it can be used as a measure of conscious perception.

The use of this specific paradigm also allows some interpretations about the role of attention in conscious perception via the interpretation of different indexes such as participants' brain responses recorded at the image frequency (6 Hz) or their performance at the detection task (detection of a change of colour of a fixation cross). At 1.5% contrast, we showed that the associated brain responses and performance to the detection task were not tied to visibility. For confidence, a linear increase in brain responses was however observed with confidence ratings. Importantly, visibility and confidence ratings may have recruited different attentional processes, notably with the alpha power impacting confidence but not subjective visibility for example (Davidson et al., 2021). However, a strict comparison between PAS and confidence is limited here because we did not perform any statistical comparison between the two measures as the mixed-models already included three independent variables. Additionally, the order of the questions was not counterbalanced across sequences (i.e., PAS judgments were always collected before the confidence judgments).

Congruently, we were surprised to observe opposite trends in how the SNR response evolved at 1% and at 1.5%. At 1% contrast, we found that the SNR at 6 Hz decreased linearly with PAS/confidence ratings. One possible explanation is that because the majority of participants were not able to perform accurately the gender-categorisation task at contrast 1%, PAS/confidence above 1 may correspond to some false alarms related to expectations occurring because sequences with contrast 1.5% and contrast 1% were embedded. Additionally, these false alarms likely involve more top-down influences with more internally-directed attention than sequences with a PAS/confidence of 1 (Zimmermann et al., 2019). As SSVEPs from flickering stimuli are reduced during internally-directed attention compared to externally-directed attention (Gjorgieva et al., 2023), this may explain why SSVEPs are reduced when PAS/confidence is higher. Similarly, the absence of difference between contrasts for SNR at 6 Hz in the accuracy model, may be explained by the low SNR for sequences associated with incorrect response at 1.5% (i.e., a contrast in which faces are overall perceived) resulting in an attentional disengagement with the sequences associated to incorrect responses (i.e., more internally-directed attention).

Generally, this work relates to the broader literature on electrophysiological indices of visual awareness such as Event-Related Potentials (ERPs), notably the Visual Awareness Negativity (VAN; Dembski et al., 2021) and the Late Positivity in face perception (LP; Lanfranco et al., 2024). Although ERPs typically allow to evaluate the timing of visual awareness in more naturalistic paradigms (i.e., do not need the repetition of a stimulus or a category of stimuli), SSVEPs benefit from a much larger SNR and reduce contamination by post-perceptual decision processes (Cohen et al., 2020).

More indirectly our results fall within the scope of the theoretical models of consciousness according to which the role of attention in conscious perception differs. For instance, in Recurrent Processing Theory (RPT), or the Higher-Order Thought (HOT) theories of consciousness (Rosenthal, 2000; Timmermans et al., 2012), a dissociation is possible between attention and consciousness, with cases in which visual representations can be formed without attention (Lau & Rosenthal, 2011), cases where individuals are conscious about stimuli under minimal attention conditions (Koivisto et al., 2006; Wyart & Tallon-Baudry, 2008), and cases in which attention is directed towards stimuli that remain unconscious, thus decorrelating attention and consciousness (Koch & Tsuchiya, 2007; Maier & Tsuchiya, 2021). In contrast, according to the Global Neuronal Workspace Theory (GNWT), attention is mandatory for any access to consciousness (Baars, 2017; Mashour et al., 2020). Our results nevertheless bring to the debate that SSVEPs are sensitive to conscious perception at the face frequency. However, it remains unclear whether this would also hold in a paradigm that directly manipulates attention across conditions, which our study did not do, since attention measures were derived across, rather than within, stimulation sequences. Future experimental protocols may thus benefit from a better tracking of potential attentional fluctuations using, for instance, the recording of pupil dilation or of microsaccade rate during sequence presentation.

Another limitation of our study is that the measure we use to assess stimulus awareness is a gender discrimination task, whereas the relevant feature in the main task is whether the stimulus is a face or not. In other words, our task falls prey to the “content criterion fallacy” identified by Michel (2023). While we recognize this limitation, we also note that gender-face categorisation can be performed in the near absence of top–down attention (Matthews et al., 2018) and seems to be considered as a relatively early process (Dobs et al., 2019) which makes this task nonetheless relevant here. Finally, assessing awareness through a face/no face detection task would have required including an additional 60 sequences with no faces in the design, which would have resulted in 120 sequences altogether—an impossible load for participants.

To conclude, the current study brings new evidence that particular instances of the FT paradigm where faces are repeated every 5th stimulus, can be used as a measure of conscious perception and hence advance our understanding of the neural correlates of conscious perception (Koch et al., 2016). Our measure was indeed sensitive to both objective and, critically, subjective perception at 1.5% contrast. This stands in contradiction with FT paradigms that use flickering stimuli which do not track conscious perception (Davidson et al., 2020). Conclusion at 1% where faces could not be categorized for the majority of the participants remains however limited because of the between-subject variability in terms of gender task performance. We also propose here that the SSVEPs at the face frequency may be mirroring the ‘true’ correlates of consciousness by minimising post-perceptual cognitive processing such as thought and judgment about the reportable properties of the stimuli and controlled attention (Tsuchiya et al., 2015). Even though our paradigm is not without any report (Frassle et al., 2014; Naber et al., 2011), we believe that the contamination of the signal by reports is limited as questions about the faces appeared after each sequence and the attentional task likely minimised introspection during sequence presentation. Because the cross was superimposed on the images, this task also guaranteed that attention was nonetheless attributed to the sequences which is crucial as inattention has been identified as an issue in no-report paradigms (Block, 2019; Duman et al., 2022) and notably abolishes binocular rivalry (Brascamp & Blake, 2012; Hancock & Andrews, 2007; Laukkonen et al., 2024; Zhang et al., 2011).

Author contributions: CRediT

- AM: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Visualization; Writing – original draft; Writing – review and editing.
- AdH: Conceptualization; Funding acquisition; Project administration; Supervision; Writing – review and editing.
- AC: Conceptualization; Supervision; Writing – review and editing.

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Scientific transparency statement

DATA: All raw and processed data supporting this research are publicly available: https://osf.io/7hkn6/files/osfstorage.

CODE: All analysis code supporting this research is publicly available: https://github.com/amazancieux/freq_tag_consciousness/tree/main.

MATERIALS: All study materials supporting this research are publicly available: https://github.com/amazancieux/freq_tag_consciousness/tree/main.

DESIGN: This article reports, for all studies, how the author(s) determined all sample sizes, all data exclusions, all data inclusion and exclusion criteria, and whether inclusion and exclusion criteria were established prior to data analysis.

PRE-REGISTRATION: No part of the study procedures was pre-registered in a time-stamped, institutional registry prior to the research being conducted. No part of the analysis plans was pre-registered in a time-stamped, institutional registry prior to the research being conducted.

For full details, see the *Scientific Transparency Report* in the supplementary data to the online version of this article.

Supplementary data

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