Examining Alpha Peak Frequency and its Relationship to Sustained Attention and Memory

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Abstract

While fluctuations in sustained attention can negatively impact immediate behavioral performance, the relationship between periods of inattention (e.g., mind wandering) and later memory is currently unclear. The current study used EEG to examine whether the peak of an individual's posterior alpha rhythm, as measured by Individual Alpha Frequency (IAF), can serve as an objective marker of inattention that predicts individual differences in long-term memory. IAF was measured during five-minutes of rest (IAF-rest) and during an incidental face-encoding task (IAF-task). We then investigated the relationship between these IAF measures and participants' (1) attentional states, as measured by objective (behavioral) and subjective (self-report) measures of inattention, and (2) subsequent memory performance. IAF was stable over time between rest and task performance, in support of past literature demonstrating IAF as a stable neurophysiological trait marker. Both IAF-rest and IAF-task correlated with fluctuations in participants' attentional state, as quantified by an objective measure of response omissions, such that participants with faster alpha oscillations demonstrated fewer response omissions. In addition, IAF-task positively correlated with subsequent memory performance, such that participants with faster alpha oscillations during encoding demonstrated better memory retrieval. Taken together, these results confirm the stability of IAF over time and suggest that individuals with higher IAF values may be better prepared to attend to incoming information and later remember it.

Keywords: attention, Individual Alpha Frequency (IAF), IAF-rest, IAF-task, long-term memory

Examining Alpha Peak Frequency and its Relationship to Sustained Attention and Memory

In a world rich with more information than the human visual system is capable of perceiving at once, we must use a filter— attention—to selectively process only the most relevant stimuli in our environment (Coutrot & Guyader, 2013). Our attentional resources, however, are limited, and in situations that demand sustained vigilance, our attention tends to fluctuate naturally between the task at hand and unrelated internal thoughts (Esterman, Noonan, Rosenberg, & DeGutis, 2013; Esterman, Rosenberg, & Noonan, 2014; Rosenberg, Noonan, DeGutis, & Esterman, 2013; Smallwood & Schooler, 2006). When our attention fluctuates inwards, we are said to be mind wandering and experience perceptual decoupling—attenuated perceptual processing of the world around us (Kam et al., 2011; Kam & Handy, 2013). These periods of inattention that occupy a third to a half of our daily lives are typically measured by having participants self-report whether their attention is on or off task and have been associated with impaired behavioral performance on sustained attention tasks, such as higher error rates and increased numbers response omissions (Carriere, Cheyne, & Smilek, 2008; Cheyne et al., 2006; Killingsworth & Gilbert, 2010; McVay & Kane, 2009; Robertson et al., 1997; Schooler et al., 2011; Smallwood et al., 2004, 2006, 2008; Stawarczyk, Majerus, Maquet, & D'Argembeau, 2011).

In addition to affecting immediate task performance, fluctuations in attention have also been linked to performance decrements that are not evident in the moment and only become evident at later periods of time. For example, a series of studies conducted by Maillet and colleagues found that self-reported inattention, defined as frequency of task-unrelated thoughts (TUTs), negatively impacts subsequent long-term memory for information encountered during a task (Maillet & Rajah, 2013; Maillet & Rajah, 2016). In one study, participants made semantic judgements about words during an incidental encoding task and self-reported their frequency of inattention (TUTs) at the end of task blocks (Maillet & Rajah, 2013). Participants then performed a retrieval task in which they viewed old and new words and had to judge whether they had previously seen the word at encoding or whether the word was new. The results revealed that a greater frequency of inattention (TUTs) during word encoding was negatively associated with subsequent memory performance in young adults. In a later experiment, Maillet & Rajah (2016) had participants perform the same basic task except they probed participants' inattention more frequently and intermittently. The results confirmed those of their 2013 study, further extending the finding that increased attentional fluctuations correlate with more source memory errors in older adults as well.

In contrast to these studies asserting that periods of inattention negatively impact later memory performance, other recent work has found no relationship between self-reported inattention and memory. In two studies conducted by Maillet and Schacter (2016, 2017), participants performed similar incidental word-encoding tasks while periodically reporting the direction of their attention. Both studies failed to find a significant relationship between frequency of stimulus-independent thoughts (SITs) and memory performance (2016, 2017). This indicates a tension in the literature between earlier studies by Maillet and colleagues that found that inattention negatively impacts subsequent long-term memory and later studies by Maillet and colleagues that found no such correlation.

In sum, while it is clear that periods of inattention negatively impact immediate behavioral performance as measured by performance errors and omissions, there is ambiguity in the existing literature as to whether fluctuations in attention impair long-term memory, particularly when performance errors are low. This ambiguity could arise from two primary sources. First, conflicting results could reflect the variability in the criteria individuals use to determine whether their attention is on or off task. In order to measure the frequency of participants' off-task attention, Maillet and Rajah (2013) presented individuals with eight questions at the end of each encoding block. In contrast, in their later studies Maillet and colleagues assessed participants' mind wandering frequencies using intermittent probes presented during encoding that asked participants to select the description that best represented their direction of attention prior to seeing the probe. The wording of the options intended to represent off-task attention varied from "mind wandering" to "having a thought that was not triggered by one of the encoding stimuli (SIT)" to "a thought that was unrelated to the task and not triggered by any task stimulus (SIT)" (Maillet & Rajah, 2016; Maillet & Schacter, 2016; Maillet & Schacter, 2017).

Another potential cause of the conflicting results in the literature is variability in individuals' meta-awareness of their task-unrelated thoughts. It is well-established that individuals have difficultly introspectively accessing their higher order cognitive processes (Nisbett & Wilson, 1977). Many studies have shown that self-report data does not accurately align with the contents of individuals' experience (Jack & Roepstorff, 2002; Jack & Shallice, 2001; Lambie & Marcel, 2002; Schooler, 2000, 2001, 2002). As renowned cognitive scientist Dr. Daniel Dennett puts it, the construct of subjective experience may simply be too elusive to be meaningfully assessed using empirical means (1991). Mind wandering is particularly difficult for individuals to subjectively assess because it is defined by a lack of experience—a redirection of attention away from external events (Schooler & Schreiber, 2004). Thus, the tension in the literature exploring the association between self-reported inattention and memory may reflect the challenges of collecting accurate self-reported assessments of cognition. The goal of the current study was to investigate whether more sensitive neural markers of inattention, specifically neural oscillations in the alpha frequency band, could serve as a more reliable predictor of individuals' subsequent memory performance.

Modulations of neural oscillations in the alpha-band are a promising candidate for capturing individual differences in attention and memory performance. The alpha band of human EEG, defined as 8.5 to 12.5 Hz, is the dominant frequency of eyes-closed waking rest—times during which an individual is awake and not engaged in any goal-directed task and mind wandering is most common (Brokaw et al., 2015; Grandy et al., 2013). Studies combing fMRI and EEG have found that alpha is strongest during rest in central and posterior regions of the brain, and have implicated alpha oscillations as a major correlate of the default mode network (DMN) (Jann et al., 2009; Jann et al., 2010a, 2010b). The DMN is believed to play a role in the self-referential thought that occurs during mind wandering and contains many of the structures that support memory processes in the brain (Brokaw et al., 2015; Jann et al., 2010a, 2010b). Research shows that increased activity of the DMN correlates with increased alpha power and higher rates of mind wandering (Jann et al., 2009; Jann et al., 2010a, 2010b; Laufs et al., 2003; Mantini et al., 2007).

In addition to alpha power, recent evidence suggests that the speed of an individual's alpha oscillations is also related to attention and behavioral performance. Individual Alpha Frequency (IAF) refers to the frequency at which an individual's alpha power peaks in the 8 to12 Hz alpha-band range (Brokaw et al., 2015; Grandy et al., 2013; Haegens et al., 2014). On average, there is a 1 Hz standard deviation in the IAF of age-matched individuals (Mierau, Klimesch & Lefebvre, 2017). Prior research has revealed that IAF is highly heritable, stable over time within individuals, and represents a strong neurophysiological trait marker of cognitive function (Grandy et al., 2013) For example, individuals with higher IAF values as measured at rest perform better on various cognitive measures involving working memory and response control (Angelakis, Lubar, & Stathopoulou, 2004; Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Clark et al., 2004). Studies conducted by Angelakis and colleagues found that individuals with higher IAF values performed better on digit span tests assessing their working memory abilities (Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Clark et al. 2004). Higher IAF values have also been associated with better memory retrieval: Klimesch, Schimke, & Pfurtscheller (1993) found that IAF as measured during retrieval was 1.25 Hz higher for individuals who performed well on a memory search task compared to individuals who performed poorly.

Recently, a study by Samaha and Postle (2015) found that IAF is positively associated with visual perceptual performance, both when IAF is calculated during a pre-task rest period and when IAF is calculated during task performance. In this study, IAF was calculated during a two-minute period of eyes-closed rest prior to task performance as well as during the pre-stimulus interval during task performance.

Individuals with higher IAFs during either of these periods demonstrated better temporal visual perception as measured by their ability to distinguish two flashes presented in rapid succession. These findings suggest that both IAF measured at rest (IAF-rest), before engagement in a cognitive task, and IAF measured during that cognitive task (IAF-task) may be predictive of task performance.

The current research explores whether participants' IAF values are related to their fluctuations in sustained attention and long-term memory performance. IAF was measured both at rest (IAF-rest) prior to task performance and during the performance of an incidental encoding task (IAF-task). During the encoding task, participants viewed faces and had to discriminate whether they were male or female. Participants were also periodically presented with an attention probe in which they reported whether their attention was on-task or off-task. Participants then performed a surprise recognition task in which they were presented with the faces they had seen at encoding as well as new faces and had to identify which faces were new and which were old. Sustained attention during the encoding task was quantified according to self-reports (i.e. subjective measure) and behavioral lapses (i.e. omissions; objective measure). Since IAF has been related to attentional fluctuations and shown to adapt to task demands, I predicted that participants with lower IAF-rest and IAF-task values would exhibit more frequent lapses of sustained attention during the task. Specifically, I hypothesized that both our (1) subjective measure of self-reported inattention during the task and (2) objective measure of inattention during the task, as measured by response omissions, would be associated with lower IAF values. In addition, I predicted that participants with lower IAF-rest and

IAF-task values will exhibit worse subsequent memory performance, as measured by lower corrected recognition scores.

Method

Participants

Thirty-three individuals were paid $15 per hour to participate in the study (17 females, 16 males, $M_{age} = 22$, $SD = 3.57$, range = 19-33, $M_{education} = 15.45$, $SD = 2.44$, range = 12-23). Participants were recruited via the online Tufts University SONA Paid database and provided written informed consent in accordance to the experimental procedures of the Institutional Review Board at Tufts University. All participants were right-handed, had normal or corrected to normal vision, were fluent in English, and reported that they had not sustained any brain injuries. One participant was excluded from all analyses because visual inspection of their frequency plot showed no alpha peak and another was excluded because of a technical error in which their resting state data failed to be recorded.

Study Design

EEG data was collected from all participants as they performed a resting state and face-memory encoding task. During the resting-state task, participants were instructed to sit in silence for five minutes with their eyes closed. After the resting-state task, participants performed a gender identification task. Participants were instructed that they would be presented with a series of faces and asked to determine whether they were male or female while hearing some tones through the speakers. Additionally, participants were informed that they would periodically be prompted to indicate whether their recent thoughts were related or unrelated to the face task. Unrelated thoughts were defined as "thoughts about the past or future, how you are feeling, etc.". Participants were told to pay attention to a central fixation cross that would appear on the monitor between the presentation of the faces and refrain from blinking except when blue brackets appeared around the cross. This blinking procedure was aimed at minimizing artifacts in the ERP data. Participants were required to press the “M” and “N” keys using their dominant hand to identify the gender of the faces and to indicate whether or not they were off or on task in response to the attention prompt. As such, participants were assigned to four different target-to-hand keyboard counterbalances. For example, a given participant may have been assigned “M for male/ yes mind wandering” and “N for female/not mind wandering”. The orientation of the keys was counterbalanced across participants.

During the gender-identification task, a total of 280 faces were presented. Before each face appeared, a fixation cross was presented on the screen followed by a tone which sounded for 100ms. After a jittered interstimulus (ISI) interval of 750 – 950ms, the face appeared in the place of the fixation cross for 1000ms. A prompt located below each face on the screen specified the participant’s response options for the gender-identification task. Following the response window, there was an ISI of 250ms during which just the fixation cross was present. Then the blue brackets appeared around the fixation cross for 750ms signaling the blinking-window. A jittered ISI period of 750-950ms preceded the next face. A total of 16 intermittent mind wandering probes appeared to assess the attentive state of the participant. The gender identification task lasted approximately 20 minutes. After the conclusion of the task, the EEG equipment was removed from the participant and they were allowed to have a short break.

In the retrieval task, the participant was shown 420 faces in total, 140 of which were “new”—meaning not presented during the gender-identification task. Participants were instructed to identify whether each face was “new” or “old” and their degree of confidence in their answer. The four options were presented in the following order from left to right under the face on the screen: old, high confidence; old, low confidence; new, low confidence; new, high confidence. The participant had as much time as needed to answer the question before the next face was shown.

The final task of the experiment was a self-paced battery of questionnaires aimed at assessing the mind wandering tendencies of the participants. These questionnaires included the CFQ-MAL (McVay & Kane, 2009), MAAS (Brown & Ryan, 2003), MWS (Mrazek, Phillips, Franklin, Broadway, & Schooler, 2013), FFMQ (Baer, Smith, Hopkins, Krietemeyer, & Toney, 2006), FST (Andrews-Hanna et al., 2013) and the SAM (Palombo, Williams, Abdi, & Levine, 2013).

EEG Data Acquisition

EEG was recorded for a five-minute resting state followed by a face-memory encoding task. EEG data was collected with the BioSemi ActiveTwo model for 32 scalp electrodes, a left eye horizontal electrooculogram(VEOG), a right eye vertical EOG (VEOG), and left and right mastoids electrodes. Surface potentials were sampled at 512 Hz.

EEG Data Preprocessing

The EEGLAB (Delorme & Makeig, 2004) and FieldTrip (Oostenveld, Fries, Maris, & Schoffelen, 2011) toolboxes were used in conjunction with written MATLAB (The MathWorks Inc., Natick, MA) scripts to preprocess and analyze the EEG data. All 32 scalp channels were first re-referenced to the average of the left and right mastoid channels. The five minutes of resting state data for each participant was epoched into

2000ms intervals for a total of 150 epochs per participant. The encoding task data was epoched from -1000ms pre-stimulus to 1000ms post-stimulus for a total of 280 epochs per participant. Data was filtered from 0.5 to 100 Hz to remove baseline drift and high frequency artifact. EEG lab was then used to automatically highlight epochs for potential rejection using peak-to-peak amplitude detection and step-like artifact detection. The peak-to-peak amplitude detection was conducted using 200ms time windows within each epoch. The window was stepped forward by 50ms intervals. A blink channel with a threshold of 75µV was created from the difference between the FP1 and the VOEG channels. Time windows that violated this threshold were flagged for detection. Step-like artifact detection was performed across all channels with a threshold of 100 µV, window size of 400ms, and a window step of 25ms. Once automatic artifact detection had flagged trials for rejection, the data was manually inspected to confirm flagged epochs had artifact and ensure any other blink, muscle, or extraneous artifacts were removed. The average number of resting state trials rejected was 19.5 (SD = 22.18) whereas the average number of clean resting state trials used for data analysis was 129.69 (SD = 22.29). Comparatively, an average of 63.29 (SD = 47.41) of the task trials were rejected while an average of 217.57 (SD = 47.41) trials were used for analysis. Power spectral density was computed for cleaned data from 0.5 to 20 Hz using a Hanning window and a 0.4 Hz frequency resolution.

Estimation of Individual Alpha Frequency

Based off of the electrodes chosen by Grandy et al. (2013) and the observed topography of where alpha power peaked across participants in the current experiment (Figure 1), IAF was calculated as the peak alpha frequency from the mean spectrum over the posterior Pz, P3, P4, T5, T6, Oz, O1, and O2 electrodes. Following the technique used by Grandy et. al (2013), peaks were defined as the points on the 7.5 to 12.5 Hz frequency spectrum where the first derivative of the curve crossed zero, thus changing from positive to negative. Two average IAF values were calculated for each participant: a mean IAF-rest value for each participant was calculated over the five minutes of resting state data collected and a mean IAF-task value was calculated as the average of the 500ms period before the onset of the face-stimuli. IAF as yoked to tones was not analyzed in the current study.

Statistical Analyses

Statistical analyses were conducted in MATLAB (MathWorks) and SPSS Version 22.0 (SPSS Inc., Chicago, IL). The relationship between variables of interest was investigated by performing Pearson Correlations, linear regression, and paired t-tests. Parametric tests were used to calculate statistical significance between conditions across participants. Directional, one-tailed tests are reported for analyses motivated by our directional hypotheses.

Behavioral Measures

Memory performance was measured via an established measure of corrected recognition—calculating the proportion of hits (old faces correctly identified as old) minus the proportion of false alarms (new faces incorrectly identified as old) (Snodgrass & Corwin, 1988). Two measures of sustained attention were used in the current experiment. An objective measure of sustained attention was calculated by measuring the number of responses participants omitted during the encoding task. A subjective measure of sustained attention was calculated based on participants' self-reported responses to the attention probes presented during the encoding task. This measure was obtained by calculating the proportion of the time participants reported off-task attention. Analysis of the battery of neuropsychological questionnaires was omitted from the present study.

Results

IAF

Thirty-one of the 32 participants for which resting state data was collected showed a visible peak in their alpha frequency during the five minutes of resting state EEG collection and were included in analysis. As expected, averaged across all participants, alpha peaked around 10 Hz in the posterior occipital-parietal regions of the brain during rest (Figure $1_{A,\ C}$). Representative examples of IAF-rest curves from six participants are displayed in Figure 1_{B}. Moreover, in support of the existing literature, there were considerable individual differences in the frequency at which participants' alpha peaked. Participants' IAF-rest values ranged from 8.0 - 11.4 Hz with the mean across all participants falling at 9.77 Hz (SD = 0.93) (Figure 1_{A}). The mean IAF-task across all participants was 9.47 Hz (SD = 1.10, range = 7.6 -11.6 Hz) and alpha again peaked in the posterior occipital-parietal regions (Figure $2_{A,\ C}$). All participants showed a visible peak in their alpha frequency during the task (Figure 2_{B}). In confirmation of the existing literature (Grandy et al., 2013), IAF was found to be stable over time: a strong positive correlation was found between participants' IAF values at rest and their IAF values during the task ($r = .61$; $p < .001$, 1-tailed) (Figure 3).

Behavior

Participants' behavioral performance is summarized in Table 1. Participants were highly accurate at making gender discriminations during the encoding task ($M_{accuracy}$ =

.95, *SD* = .04). However, participants reported being off-task in response to 69% of the attention probes and there was substantial variability in the number of trails participants omitted during the encoding task (*M* = 5.45, *SD* = 8.02). This high rate of self-reported inattention is consistent with past research that found that participants frequently mind wander even during simple cognitive tasks (Giambra, 1995; Teasdale et al., 1993). Analysis of participants' subsequent memory performance revealed that their average proportion of hits was .42 (*SD* = 0.04) whereas their average proportion of false alarms was .32 (*SD* = 0.12). This translates to an average corrected recognition score of .09 (*SD* = 0.08) across participants. Neither participants' number of omissions ($r = -.32$; $p = .08$) nor their self-reported inattention ($r = .13$; $p = .46$) correlated with their corrected recognition scores.

Relationship Between IAF and Behavior

A summary of the correlations between IAF and the behavioral measures of memory and attention is presented in Table 2. In support of our hypothesis, IAF-rest negatively correlated with omissions, our objective measure of inattention ($r = -.43$; $p < .01$; 1-tailed), revealing that participants with lower IAF values at rest had more frequent omissions during the encoding task (Figure 4). Likewise, a significant negative correlation was observed between IAF-task and omissions ($r = -.41$; $p = .01$; 1-tailed) (Figure 5). In contrast, our subjective measure of inattention, operationalized as the rate of off-task self-reports during the encoding task, did not correlate with participants' IAF-task ($r = .24$; $p = .10$; 1-tailed) and positively correlated with participants' IAF-rest ($r = .33$; $p = .03$; 1-tailed). To further examine the contribution of IAF-rest and IAF-task to objectively-measured fluctuations in attention, hierarchical multiple regression was performed with omissions entered as the dependent variable and IAF-rest and IAF-task entered as predictors. As reported above, IAF-rest was a significant predictor of attentional performance as measured by omissions. Adding IAF-task to the second step of the model did not improve its capacity to account for variance in attentional performance (R^2 change = .03, F (1,28) = 1.13, p = .30). In terms of memory performance, there was no correlation between IAF-rest and later performance on the subsequent memory task as measured by corrected recognition (r = .14; p = .23; 1-tailed) (Figure 6). However, a positive correlation was observed between IAF-task and memory (r = .34; p = .03, 1-tailed) (Figure 7).

Discussion

The current study investigated whether individual variability in the speed of alpha oscillations at rest (IAF-rest) and during incidental encoding (IAF-task) are linked to fluctuations in sustained attention and subsequent long-term memory performance. As expected from the existing literature, alpha oscillations were greatest over the posterior occipital-parietal regions of participants' brains and there was substantial variability in the alpha peak frequency across individuals. Additionally, IAF-rest was positively correlated with IAF-task across individuals, confirming the high stability of IAF over time observed in prior studies (Grandy, 2013). In terms of sustained attention, we found a negative relationship between IAF and our objective measure of inattention—response omissions—such that individuals with lower IAF values omitted more responses during the encoding task. In contrast, our subjective measure of inattention—rate of off-task self-reports—did not negatively correlate with participants' IAF-task or IAF-rest. In terms of subsequent memory, we found no relationship between IAF-rest and memory performance. However, a positive relationship was found between IAF-task and memory performance, such that individuals with lower IAF values during the incidental encoding task had reduced subsequent memory. Together, these results provide novel evidence for a close relationship between the speed of alpha oscillations and both sustained attention and memory.

IAF Predicts Attentional Fluctuations According to Objective but Not Subjective Measures

Our finding that individuals with lower IAF values have more frequent periods of inattention, as measured by omissions, is consistent with prior studies that have linked IAF and other objective measures of immediate behavioral performance. Grandy et al. (2013) found that individuals with higher IAF values at rest performed better than individuals with lower IAF values on twelve tasks assessing various cognitive abilities including perceptual speed and working memory. In line with the results of the current study and specific to the realm of attention, a prior study found that individuals with lower IAF values demonstrated worse response control on a reading task (Angelakis, Lubar, & Stathopoulou, 2004). Importantly, the current study mirrors the results of Samaha and Postle (2015) in showing that both IAF measured at rest prior to task performance (IAF-rest) and pre-stimulus IAF during task performance (IAF-task) are predictive of behavioral performance on a cognitive task. Whereas Samaha and Postle (2015) demonstrated this association in the realm of perception, the current study is the first to suggest that IAF can reliably predict individual variability in sustained attention.

While IAF-rest and IAF-task were negatively associated with lapses in sustained attention according to our objective measure of omissions, our subjective measure of inattention—rate of off-task self-reports—did not significantly correlate with participants' IAF-task. Furthermore, contrary to our hypothesis, a positive correlation was found between subjective self-reports of inattention and participants' IAF-rest, whereby participants with lower IAF values had *fewer* off-task reports. This failure to find a consistent association between lower IAF and higher self-reported inattention may be due to the unreliability of this subjective measure. According to Schooler and Schreiber (2004), individuals' self-reports of their off-task attention may not accurately measure their experienced frequency of mind wandering during a task. Research shows that due to the challenging nature of introspectively accessing our own higher order cognitive processes, we are only intermittently aware of when our minds are wandering (Schooler et al., 2011). Therefore, participants' reports of off-task attention may not have accurately reflected their experienced rate of mind wandering in the current task. In contrast, our objective measures of inattention (omission) may be able to more accurately capture fluctuations in attention. Indeed, Schooler and Schreiber (2004) urge the importance of measuring the degree to which self-reports co-vary with other environmental, behavioral, and physiological measures of inattention given the difficulty of assessing mind wandering with subjective self-reports.

Task IAF is Associated with Subsequent Memory Performance

In addition to finding a relationship between IAF and omissions, we also found a relationship between IAF and subsequent memory performance. Prior research has provided preliminary support linking IAF and memory performance. In a study by Klimesch, Schimke, & Pfurtscheller (1993), the IAF values of individuals who performed well on a memory search task was found to be 1.25 Hz higher than the IAF values of individuals who performed poorly. However, IAF in this study was only measured at retrieval, not when information was being encoded into memory or at rest. In the current study, a significant positive relationship was found between pre-stimulus IAF measured during memory encoding and subsequent long-term memory performance, such that individuals with higher IAF values demonstrated better subsequent memory. Thus, the current results extend the findings of Klimesch, Schimke, and Pfurtscheller (1993) and reveal that in addition to predicting attentional fluctuations during a task, background alpha oscillations also predict the success of memory encoding. Put in the context of prior research pointing to a positive relationship between IAF and working memory, this finding suggests that IAF is associated with performance on tasks involving many different kinds of memory (Angelakis, Lubar, Stathopoulou, & Kounios, 2004; Clark et al., 2004, Grandy et al. 2013). Interestingly, we did not find an association between IAF-rest and subsequent memory. This result suggests that while IAF at rest and during task engagement are strongly correlated, subtle changes in IAF can occur when attention is directed to an external task and can influence memory encoding.

Interpretation and Conclusion

The current study represents an important step towards exploring the poorly studied relationship between IAF, attentional fluctuations, and memory. Moreover, the current study is the first to examine the relationship between memory and IAF measured both before a task (IAF-rest) and during a task (IAF-task). As such, we were able to confirm the high stability of IAF implicated by past research by finding that individuals with higher IAF-rest values also had higher IAF-task values (Grandy, 2013). Importantly, the lack of association we found between both our objective (omissions) and subjective (self-report) behavioral measures of attention and memory performance emphasized the need to identify an objective neural marker of inattention that predicts memory performance. Our finding that higher IAF-rest and IAF-task values were correlated with fewer objectively measured attentional fluctuations (omissions) during a cognitive task adds to the existing body of literature positively associating IAF with enhanced performance on cognitive tasks.

There are several practical implications that arise from the novel finding that IAF appears to be an objective neural marker of attentional fluctuations and subsequent memory. Attending to information and encoding it into memory is crucial for navigating daily life. For example, when we are introduced to new people it is important we recognize their faces later on. Yet research clearly shows that we spend a substantial amount of time not attending to what is going on in the external environment around us: the average young adult spends a third to half of their time mind wandering (Kane et al., 2007; Klinger & Cox, 1987-1988; Killingsworth & Gilbert, 2010; McVay, Kane, & Kwapil, 2009). Moreover, there are individual differences in our how frequently we mind wander and our capacities for directing and sustaining attention (Kane et al., 2007; McVay & Kane, 2009, 2012a,2012b; Shaw & Giambra, 1993). Identifying an objective neural marker of inattention that predicts memory is as crucial step towards developing interventions that could help us decrease the frequency of our attentional fluctuations and the amount of information we later forget.

In addition to its practical implications, the current study has important implications for better understanding the nature of IAF. The fact that IAF was associated both with fluctuations in sustained attention and long-term memory suggests that IAF may play a role in preparing individuals to attend to incoming information, as Angelakis and colleagues (2004) previously suggested. In this sense, individuals with higher IAF values may be more "prepared" to attend to incoming information and thus omit fewer responses. A more prepared cognitive state may entail less distraction by internal thoughts and thus better attention to the surrounding world. Likewise, the fact that higher IAF values are associated with better temporal visual discrimination could mean that individuals with higher IAF values are better prepared to process that visual information (Samaha & Postle, 2015). This proposal aligns with the result of Samaha and Postle (2015) in which individuals with faster alpha oscillations were able to distinguish between two closely presented visual stimuli. They suggested that individuals with higher IAF values may be able to distinguish these stimuli because they fall on different alpha phase cycles, a reflection of the perceptual system's enhanced ability to separate and process incoming information in the environment.

Despite the strength of this study in expanding earlier research and its practical implications, it has some limitations that could be addressed by further research. Most importantly, our results should be considered preliminary and should be interpreted with caution given that our statistical tests were not corrected for multiple comparisons. Additionally, this study is limited by the fact that the mean age of our participants was 22 year olds. Prior studies have found that IAF values are lower in older adults compared to younger adult samples (Grandy, 2013). An important area for future research is to see whether older adults also demonstrate a similar relationship between IAF and attention as well as IAF and memory. Additionally, the study by Maillet and colleagues (2016) found that young and older adults differ in terms of how frequently they self-report mind wandering in a task. In addition, age-related differences in the relationship between self-reported mind wandering and subsequent memory were found. As such, an important area for future research will be to test whether the current findings extend to older adults. In addition to addressing the limitations of the current study, future studies should also investigate the relationship between long-term memory and other aspects of alpha oscillations beyond frequency. Other characteristics of alpha, such as fluctuations in power, may be more sensitive indices that relate to long-term memory performance. Indeed, analysis of our participants' alpha peak frequency plots show great individual variability in alpha power at the peak frequencies (Figures 1 and 2). However, preliminary analyses investigating the relationship between alpha power and memory across individuals did not reach significance. That said, alpha could be split into two further subdivisions—a lower alpha band defined as 8.5 to 10.5 Hz and an upper alpha band defined as 10.5 to 12.5 Hz. Recent studies have confirmed differences in the networks with which the upper and lower bands are associated. Activity in the Frontal Attention Network and Dorsal Attention Networks has been associated with increased lower alpha band activity whereas activity in the DMN has been associated with increased upper alpha band activity (Jann et al., 2009, 2010). Studies by Klimesch further found that upper alpha desynchronization is positively correlated with semantic long-term memory performance (1996, 1999). Thus, one prediction may be that analyses of the relationship between alpha power, inattention, and long-term memory may prove significant when analyzing the upper and lower alpha bands separately.

In conclusion, the current study provides exploratory evidence that IAF may serve as a neural marker predictive of background attentional fluctuations and long-term memory. Higher IAF values may reflect a state of greater cognitive capacity and preparedness to process and remember incoming information. Future research should look to confirm the predictive value of IAF for inattention and later forgetting, as well as continue exploring other measures of alpha as potential markers of inattention and long-term memory. Despite the limitations of the current study, it represents a novel step towards identifying an objective predictor of inattention and memory.

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Table 1: *Behavioral Measures Assessing Participant's Sustained Attention and Subsequent Memory*

	Average (SD)	**Range**
Gender Task Accuracy	.95(.04)	.86 - .99
Proportion of Hits	.42(.12)	.10 - .60
Proportion of False Alarms	.32(.12)	.04 - .50
Corrected Recognition (Proportion H - Proportion FA)	.09(.08)	-.02 - .30
Proportion Off-Task Reports	.69(.27)	0 – 1
Omissions	5.45(8.02)	0 – 30

Table 2. *IAF-Rest and IAF-Task Correlated with Memory and Attention Performance*

	Memory (Corrected Recognition)	**Attention**	
		Off-Task Reports	**Omissions**
IAF-Rest	$p = .23$ $r = .14$	$p = .03$* $r = .33$	$p < .01$* $r = -.43$
IAF-Task	$p = .03$* $r = .34$	$p = .10$ $r = .24$	$p = .01$* $r = -.41$
IAF-Rest vs. Task	$p < 0.001$* $r = .61$		

Note. One-tailed tests of significance are reported given directional hypotheses. * $p < .05$

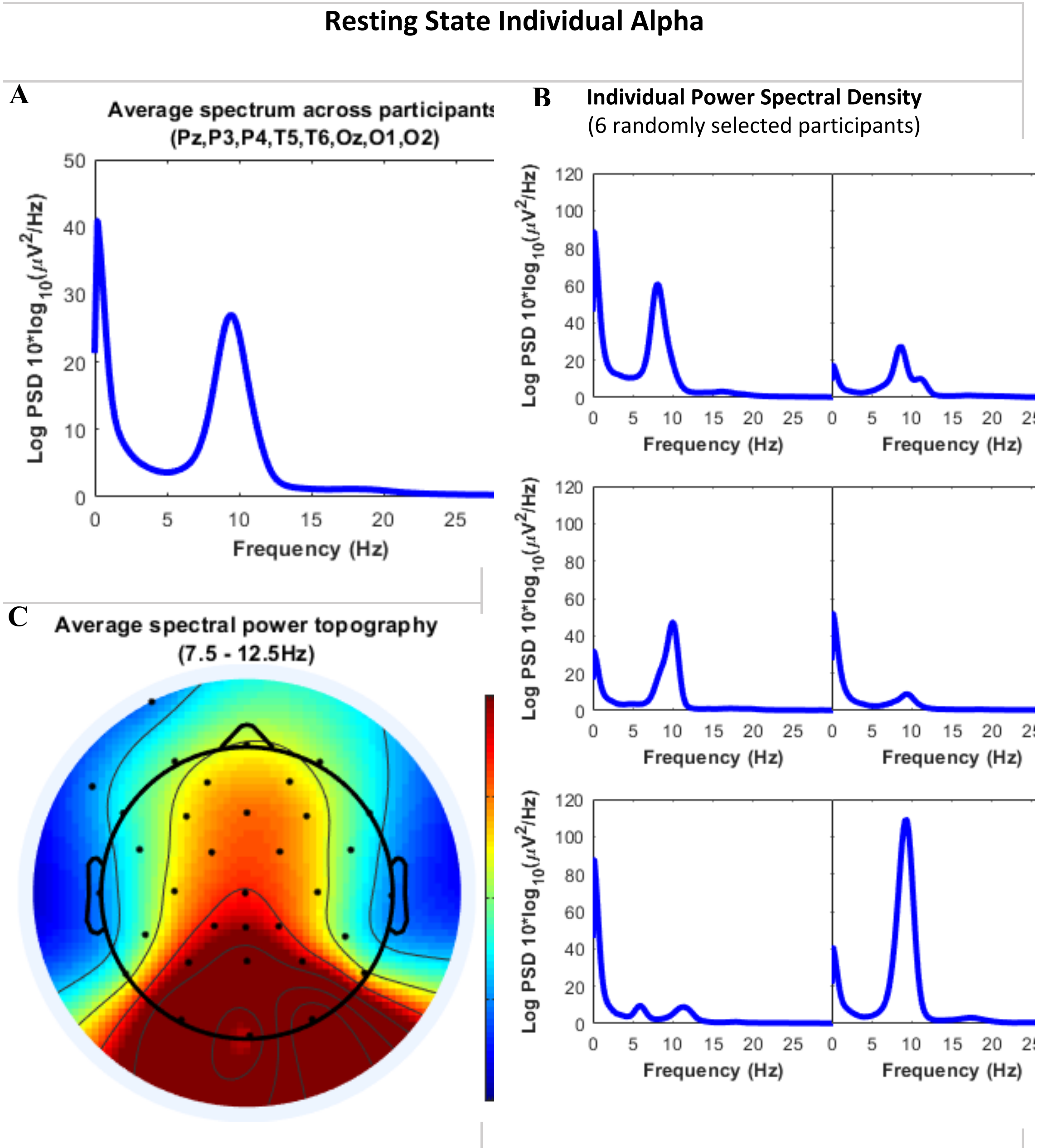

Figure 1. A: Curve representing average resting state alpha peak across participants averaged across electrodes Pz, P3, P4, T5, T6, Oz, O1, and O2. B: Topography of average spectral power ranging from 7.5 to12.5 Hz. Scaled from 0 to 15 dB. C: IAF-rest curves of six individual participants.

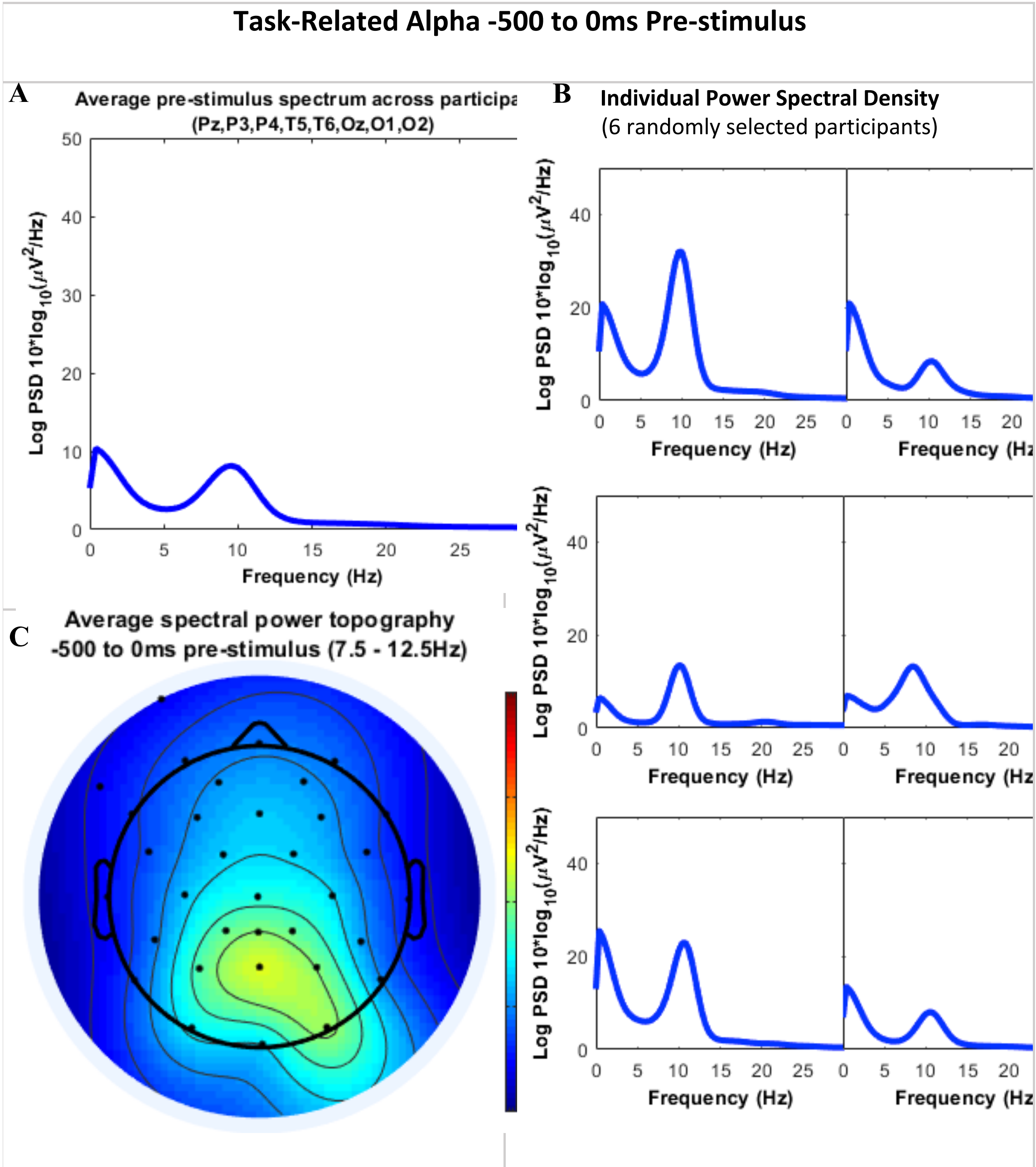

Figure 2. A: Curve representing average task alpha peak across participants averaged across electrodes Pz, P3, P4, T5, T6, Oz, O1, and O2. B: Topography of average spectral power ranging from 7.5 to 12.5 Hz. Scaled from 0 to 15 dB. C: IAF-task curves of six individual participants.

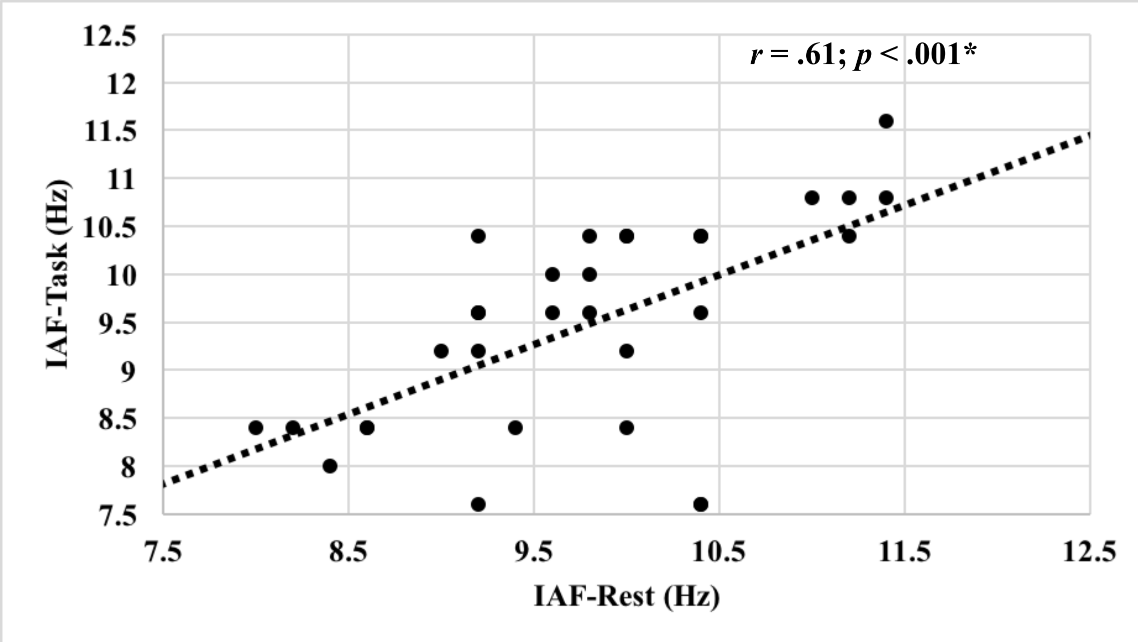

Figure 3. Relationship between IAF-task and IAF-rest.

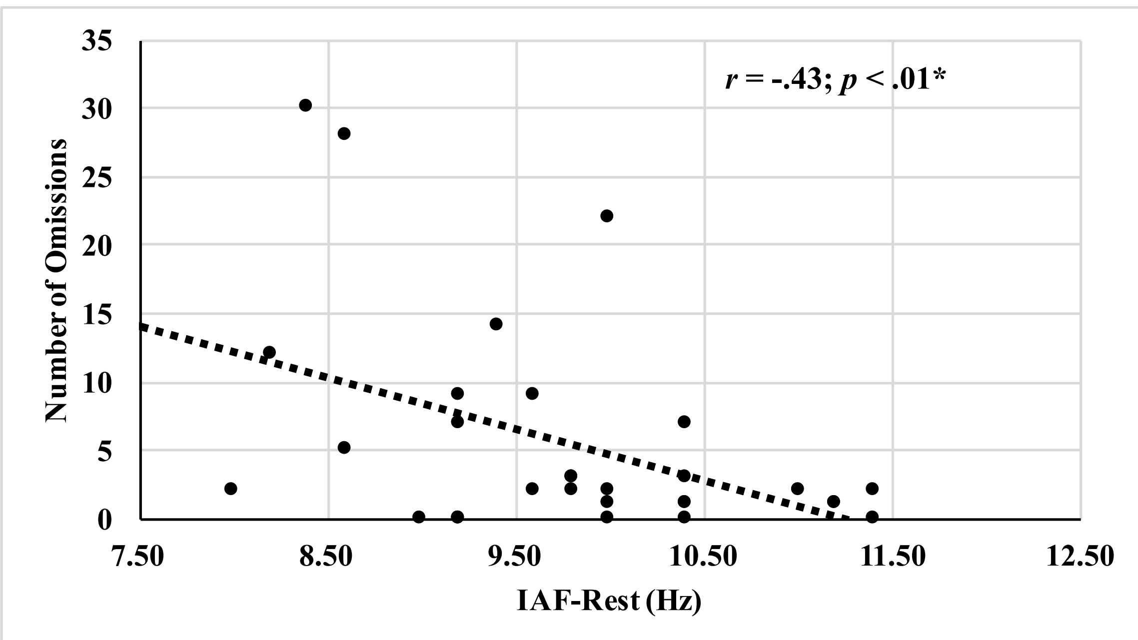

Figure 4. Relationship between IAF-rest and omissions.

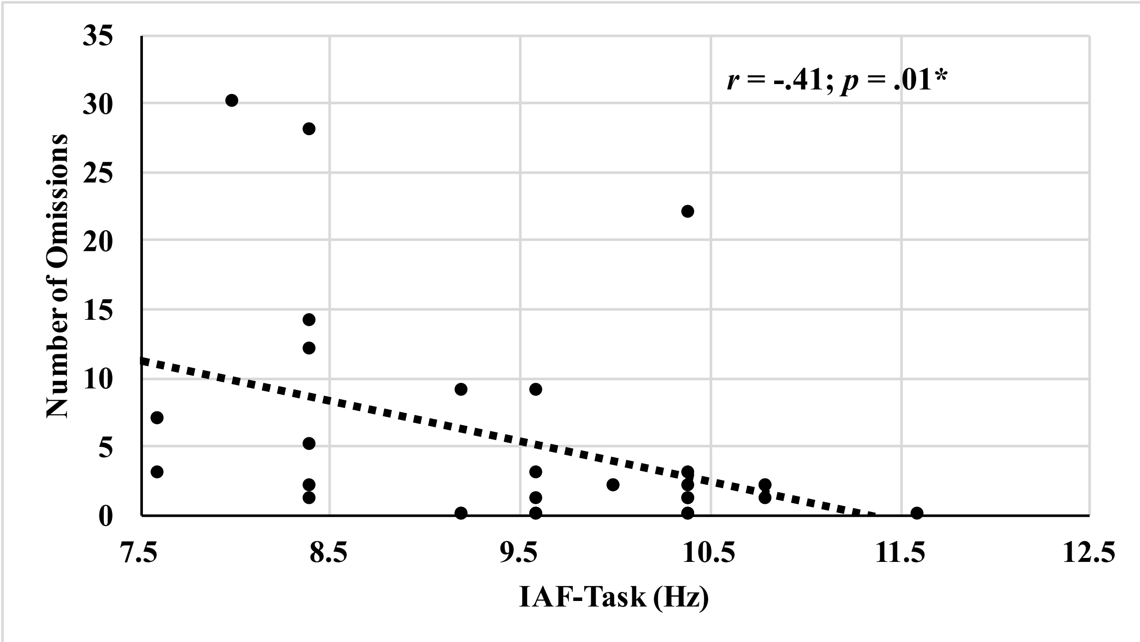

Figure 5. Relationship between IAF-task and omissions.

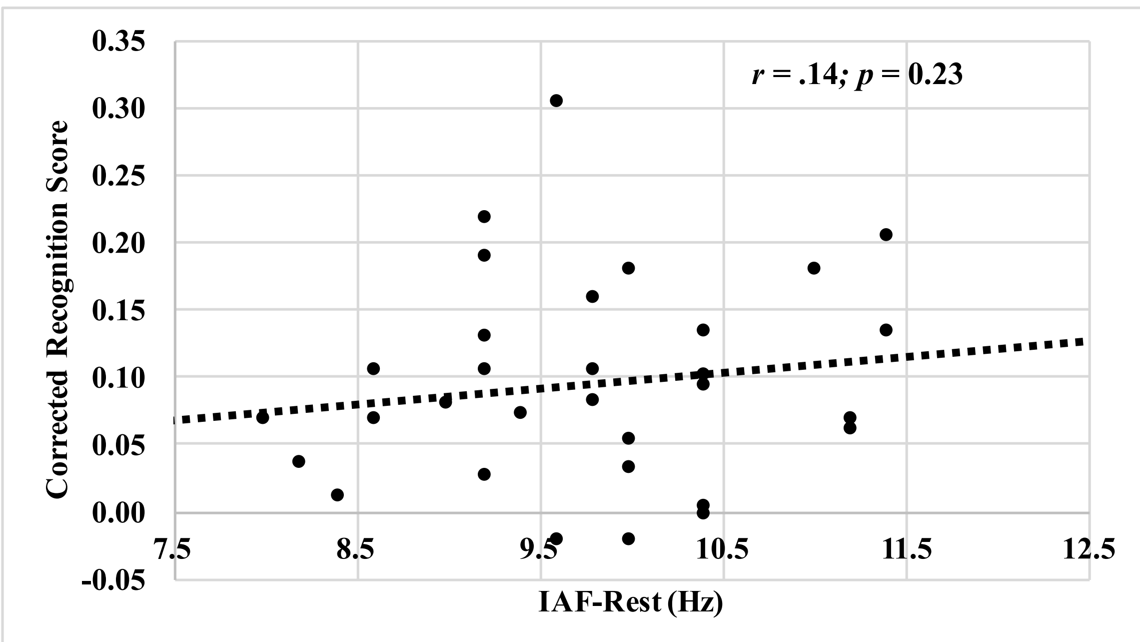

Figure 6. Relationship between IAF-rest and corrected recognition memory.

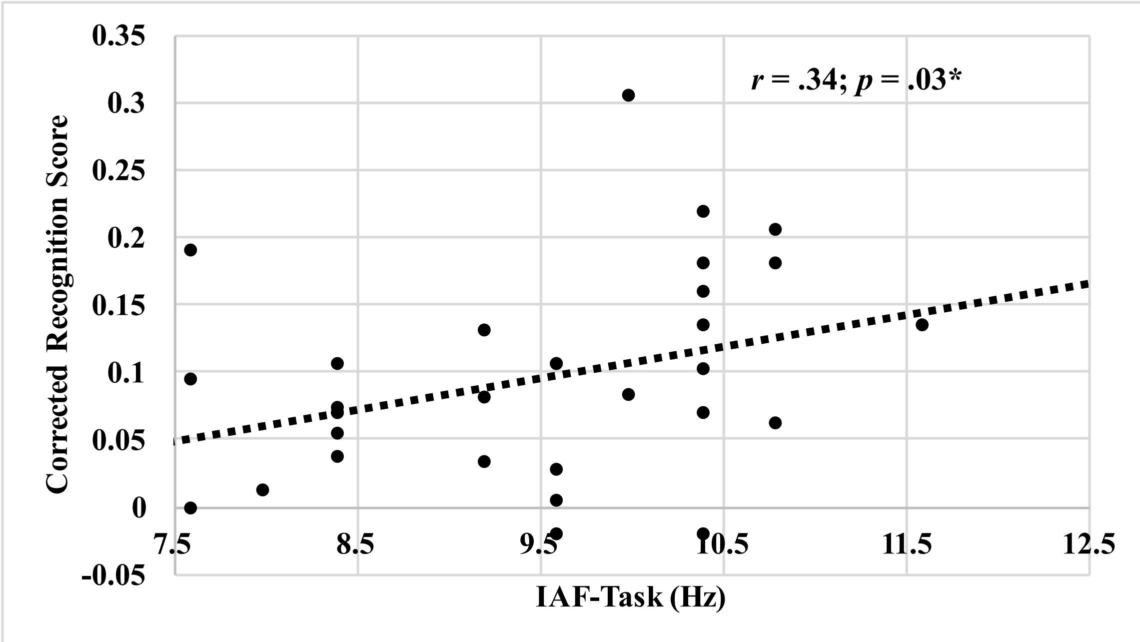

Figure 7. Relationship between IAF-task and corrected recognition memory as measured by the proportion of hits minus the proportion of false alarms.