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RESEARCH REPORT

# Trial-to-Trial Fluctuations in Attentional State and Their Relation to Intelligence

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Trial-to-trial fluctuations in attentional state while performing measures of intelligence were examined in the current study. Participants performed various measures of fluid and crystallized intelligence while also providing attentional state ratings prior to each trial. It was found that pre-trial attentional state ratings strongly predicted subsequent trial performance on the fluid intelligence measures, such that when participants rated their current attentional state as highly focused on the current task, performance tended to be high compared to when participants reported their current attentional state as being low and unfocused on the current task. Furthermore, overall attentional state ratings and variability in attentional state ratings were moderately correlated with overall levels of performance on the fluid intelligence measures. However, attentional state ratings did not predict performance on the measure of crystallized intelligence. These results suggest a strong link between variation in attention state and variation in fluid intelligence as postulated by a number of recent theories.

*Keywords:* intelligence, attention, fluctuations



Individual differences in intelligence have long been a key research topic in psychology and other disciplines. Variation in intelligence has been found to be an important predictor of a number of real world behaviors including performance in educational and professional settings (Deary, Strand, Smith, & Fernandes, 2007; Schmidt & Hunter, 1998) as well as overall health and mortality (Gottfredson & Deary, 2004). In particular, the concept of general fluid intelligence (gF), which is the ability to solve novel reasoning problems, has been extensively researched and shown to correlate with a number of important skills (Cattell, 1971). As such, understanding the nature of variation in gF has become an essential topic of research.

Recent work has suggested that working memory capacity (WMC) and attention control abilities are critical components of gF and partially account for individual differences in gF (Kane & Engle, 2002; Unsworth & Engle, 2007). For example, recent work has consistently found substantial correlations between latent variables of WMC and gF leading researchers to suggest that WMC accounts for roughly 50% of the variance in gF (Kane, Hambrick, & Conway, 2005). According to attention control theories, control is needed to actively sustain attention on the task and to maintain task goals in the presence of potent internal and external distraction that can capture attention (Kane & Engle, 2002; Unsworth & Engle, 2007). As such, attention control theories suggest that the relation between WMC and gF is due to the fact that gF tests require a high degree of attention control in order to allow for successful performance. Recent work has provided evidence consistent with this view by demonstrating strong correlations between latent variables of attention control and gF and by demonstrating that the strong relation between WMC and gF is partially due to variation in attention control abilities (Unsworth & Spillers, 2010; Unsworth, Spillers, & Brewer, 2009). Thus, this work suggests that attention control abilities are important predictors of performance on measures of gF.

Despite this initial evidence for a link between attention control and gF, little is known about how variation in attention control is related to gF. Clearly there are a number of important components to attention control, each of which would be needed for successful performance on a measure of gF. In the current study, we examine one component in particular (trial-to-trial fluctuations in attention) in order to determine whether it is an important predictor of gF performance. Specifically, it is a common assumption that attention waxes and wanes during a task in which attention is initially focused on the task, but slowly wanes as our minds wander or we become distracted, then attention once again focuses back on the task at hand (e.g., Gilden, 2001; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997). These trial-to-trial fluctuations of attention have been found to occur in a number of prolonged tasks, and research suggests that participants' self-reports of their attentional state are reliable and valid (Smallwood & Schooler, 2006). Specifically, a number of studies have utilized thought-probe techniques in which periodically during a prolonged attention task (such as the Sustained Attention to Response Task; Robertson et al., 1997) participants are probed and are required to

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report whether their attention was currently focused on-task or whether they were mind-wandering. This research has consistently found that not only do participants report extensive mind-wandering during attentional tasks but also that these self-reports of attentional state are correlated with actual performance, such that self-reports of less focused attention (i.e., more mind-wandering) are associated with lower levels of performance (e.g., McVay & Kane, 2009; Schooler, Reichle, & Halpern, 2004). Particularly relevant to the current work, Mrazek et al. (2012) found that participants reported mind-wandering during measures of fluid intelligence and, importantly, that these mind-wandering self-reports were negatively related to performance such that participants who reported more mind-wandering performed more poorly on the intelligence measures.

In another recent study, Macdonald, Mathan, and Yeung (2011) examined trial-to-trial fluctuations in attentional state in a rapid serial presentation detection task by probing participants after each trial (rather than randomly throughout the task) and found that fluctuations in subjective attentional state strongly predicted performance such that when pre-trial attentional state ratings were high, performance was relatively good, and when pre-trial attentional state ratings were low, performance was worse. Furthermore, Macdonald et al. found that subjective attentional state ratings were negatively related with prestimulus electroencephalography (EEG) alpha power, suggesting that fluctuations in attention are reflected in not only subjective ratings but also in EEG alpha power.

Given the link between attention control and gF, and the notion that trial-to-trial fluctuations in attentional state are associated with performance on prolonged tasks requiring the control of attention, it seems possible that fluctuations of attention likely occur while participants are performing gF tasks and that these fluctuations could be strong predictors of not only overall levels of performance but also performance on an individual trial basis. That is, overall levels of attentional state should not only predict overall levels of performance on such tasks, but each pre-trial attentional state rating should predict performance on that trial. When participants are strongly focused on the task they should be more likely to solve a given problem than when they are not as focused on the task. Furthermore, these effects should only arise on tasks that require a great deal of focused attention for performance. That is, tasks that rely on more automatic processes or basic knowledge retrieval should not demonstrate a relation between attentional state and performance because a participant's current attentional state should not matter much for performance. For example, consider general crystallized intelligence (gC), which is the ability to use prior knowledge to solve the current problem (Cattell, 1971). Vocabulary tests are the quintessential measure of gC. The amount of current attentional focus will likely have little impact on performance on a basic vocabulary test. That is, you either know the definition of the word "diatribe" or you do not. Focusing more on the task will not provide you with the answer if the answer is not stored in your long-term memory. Thus, although there are surely trial-to-trial fluctuations in attentional state on such tasks, these fluctuations are unlikely to impact performance much. This notion is consistent with the context regulation hypothesis, which suggests that fluctuations in attention (particularly mind-wandering) are more likely to interfere with performance on tasks that require a great deal of attentional focus (Smallwood, 2013). Overall, this line of reasoning suggests that trial-to-trial fluctuations in attentional state should predict performance on gF measures but not necessarily on gC measures. These notions were explored in three experiments. In each experiment, participants performed standard measures of intelligence, and prior to each trial participants rated their current attentional state on scale of 1–10.

## Experiment 1

To examine possibility that fluctuations in attention state predict performance on gF measures, participants performed the Raven Advanced Progressive Matrices (APM; Raven, Raven, & Court, 1998), which is perhaps the most well-known measure of gF. In this task, participants are presented with a matrix of geometric patterns with the bottom right pattern missing. The task for the participant is to select among eight alternatives the one that correctly completes the overall series of patterns. In one condition, participants performed the APM under normal conditions. In the other condition, participants performed the same APM, with the exception that prior to each trial, participants were instructed to provide a numerical rating (1–10) on their current attentional state. The reason for including a condition where participants did not provide attentional state ratings was to examine possible reactivity effects whereby providing attentional state ratings could lead to changes in performance to more standard versions of the APM. If there are no differences between the two conditions, we can assume that the attentional ratings provide a window into normally ongoing processes in the APM. Overall then, if the ability to sustain and maintain attention on task is an important component for successful performance on gF measures, then we should see that fluctuations in subjective attentional state strongly predict overall and trial-to-trial levels of performance.

### Method

Participants were 104 undergraduate students recruited from the subject pool at the University of Oregon. Participants were randomly assigned to one of the two conditions (control condition, $n = 53$; attentional state condition, $n = 51$). Participants were between 18 and 35 years of age and received course credit for their participation. Each participant was tested individually in a laboratory session lasting approximately 1 hr. All participants performed the same computerized version of Set II of the APM, with the exception that participants in the attentional state condition provided attentional state ratings prior to each trial. The APM consists of 36 individual items presented in ascending order of difficulty (i.e., the easiest item is presented first and the hardest item is presented last). Each item consists of a display of $3 \times 3$ matrices of geometric patterns with the bottom right pattern missing. The task for the participant is to select among eight alternatives the one that correctly completes the overall series of patterns. Participants were allotted 30 min to complete as many items as possible. In the attentional state condition, participants were informed that we were also interested in their overall attentional state in the task. Therefore, before each problem, they were asked to indicate their attentional state for the current trial only on a 1–10 scale, with a 1 indicating that they were *not at all focused on the current task*, a 5 indicating that they were *somewhat focused on the current task*, and a 10 indicating that they were *totally focused on the current* *task*. While making the ratings, they were told to incorporate the amount of mind wandering and distraction into a single value similar to Macdonald et al. (2011). Participants provided their attentional state ratings by typing in a number from 1 to 10 and pressing enter to record their response. Immediately after giving their attentional state rating the next trial appeared.

## Results and Discussion

First, we examined overall differences in performance between the two conditions to examine any reactivity effects due to providing attentional state ratings. As can be seen in Figure 1, performance dropped as trial number increased, as is typically seen, and there were no differences between the two conditions in performance. Specifically, overall levels of performance were similar for the control ($M$ = 20.36, $SD$ = 6.03) and attentional state ($M$ = 20.22, $SD$ = 5.99) conditions, $t(102) = 0.12$, $p > .90$, $\eta^2 = .001$.

Given that there did not seem to be any reactivity effects associated with providing attentional state ratings, we next focused only on the attentional state condition to better examine whether pre-trial attentional state ratings predict performance. First, we examined whether there was a relation between pre-trial attentional state and accuracy on the Raven problems. Because not all participants utilized the entire rating scale, we used linear mixed models to analyze the data. Linear mixed models are an extension of the general linear model in which both fixed and random effects are included. Thus, they are similar to mixed analysis of variance (ANOVA) but offer advantages over traditional mixed ANOVAs in terms of more power and the ability to handle unbalanced designs and missing data (e.g., Kliegl, Wei, Dambacher, Yan, & Zhou, 2011). In the model, attentional state was entered as a fixed factor, and subjects were entered as random factors. As shown in Figure 2a, there was a strong linear effect of attentional state on accuracy, $t = 10.39$, $p < .001$ ($b = .08$, $SE = .01$). This suggests that when attentional state was high, participants performed much better than when attentional state was low.

Because item difficulty increases throughout the task (see Figure 1), we also examined attentional state ratings as a function of trial number. That is, we examined attentional state as a dependent variable. As shown in Figure 3, attentional state ratings decreased throughout the task, $t = -16.9$, $p < .01$ ($b = -.05$, $SE = .01$). Thus, it is possible that the relation between attentional state and proportion correct might be due to changes in attentional state as a function of problem difficulty. That is, the attentional state ratings are high at the beginning of the task when problems are easy, and as the difficulty increases and accuracy decreases, so too might attentional state ratings. To better examine this, we examined the relation between attentional state ratings and performance for the first and second halves of the task. As shown in Figure 2b, the positive relation between pre-trial attentional state ratings and performance was similar for both the first and second halves of the task. Specifically, entering half as a fixed factor in the linear mixed model suggested that there was an effect of attentional state ($b = .04$, $SE = .02$, $t = 2.16$, $p < .05$), an effect of half ($b = -.40$, $SE = .08$, $t = -5.26$, $p < .01$), but no interaction between the two ($t = -.26$, $p > .79$). Thus, pre-trial attentional state ratings predicted task performance even when taking changes in overall difficulty levels into account. Another way of examining this is to specifically examine the effect of trial number on accuracy and whether trial number interacts with attentional attentional state. Therefore, we ran the same linear mixed model but with trial number entered as a fixed effect instead of half. Similar to the analysis examining half, the results suggested an effect of attentional state ($b = .04$, $SE = .01$, $t = 2.98$, $p < .05$), an effect of trial number ($b = -.02$, $SE = .01$, $t = -5.39$, $p < .01$), but no interaction between the two ($t = -1.20$, $p > .23$).

Next, we examined whether individual differences in overall attentional state would predict performance on the APM. Descrip-

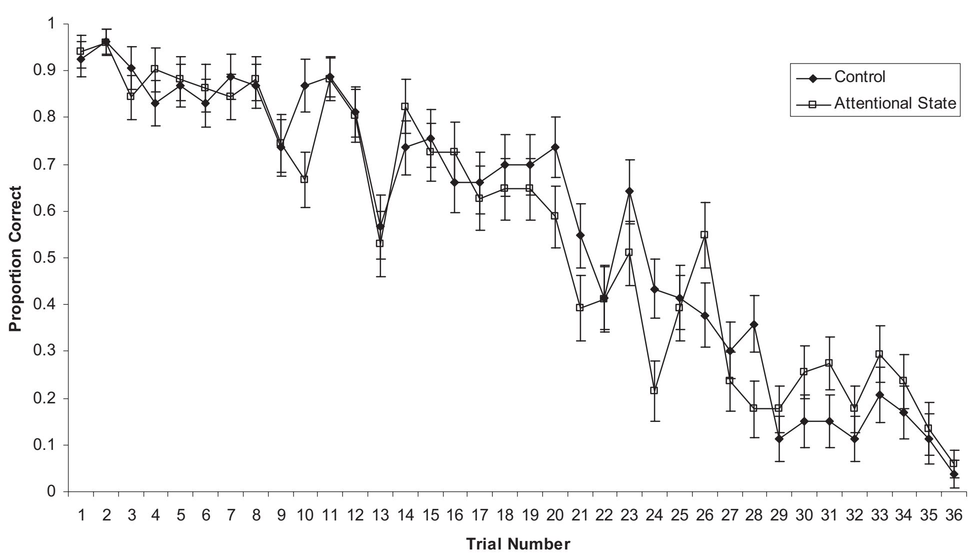


*Figure 1.* Mean proportion correct for individual Raven problems as a function of condition in Experiment 1. Error bars represent one standard error of the mean.

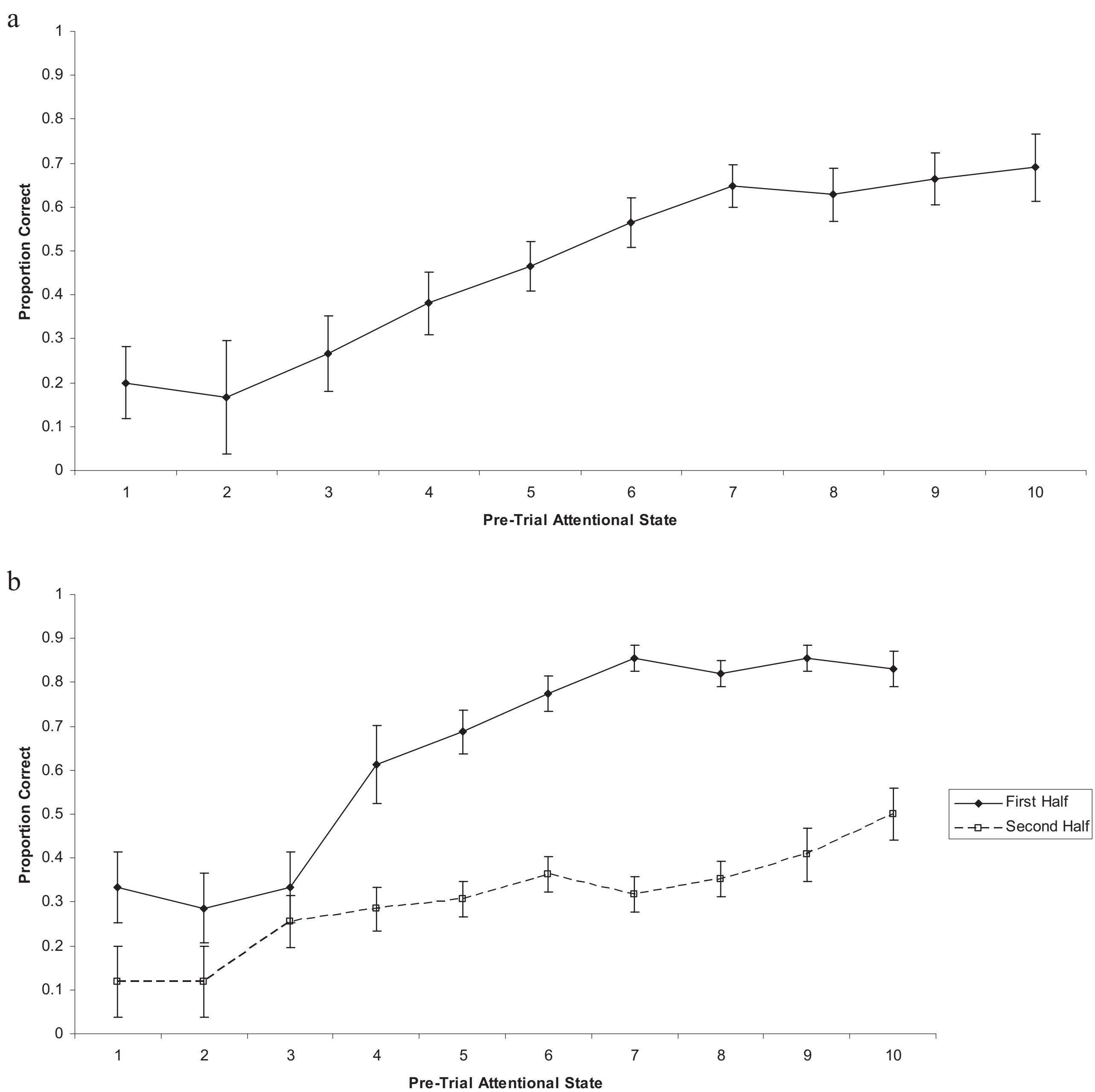


*Figure 2.* (a) Mean proportion correct for the Raven as a function of attentional state for the entire Raven task in Experiment 1. (b) Mean proportion correct for the Raven as a function of attentional state and as a function of first half and second half of the task in Experiment 1. Error bars represent one standard error of the mean.

tive statistics are shown in Table 1. There was a moderate positive correlation ($r = .43$, $p < .01$) between participants' attentional states and overall accuracy levels on the APM. Thus, participants who reported higher attentional states throughout the task tended to perform better than participants who reported lower attentional states throughout the task. We also examined whether variability in attentional state would predict performance, assuming that individuals who demonstrate more fluctuations in attentional state (i.e., more lapses of attention) would likely perform more poorly than individuals who can sustain their attention throughout the task (Unsworth, Redick, Lakey, & Young, 2010). Therefore, we computed each individual's standard deviation for his or her attentional state ratings and correlated this with each individual's total number of correct solutions. There was a moderate negative correlation ($r = -.32$, $p < .01$) between each individual's standard deviation of attentional state ratings and overall levels of performance. Mean attention state and the standard deviation of attentional state were also correlated ($r = -.50$, $p < .01$). This suggests that not only do

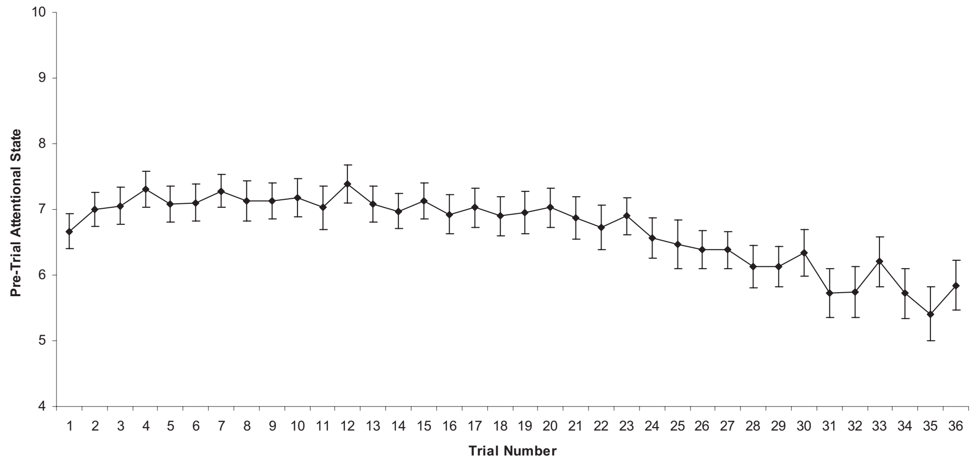


*Figure 3.* Pre-trial attentional state ratings as a function of trial number in Experiment 1. Error bars represent one standard error of the mean.



individuals who score high on the APM have higher overall attentional states but that these individuals also demonstrate fewer fluctuations in attentional state than individuals who score low on the APM. Indeed, shown in Figure 4 are the attentional state ratings for the highest scoring participant and the lowest scoring participants as a function of trial number. As can be seen, the lowest scoring participant not only has overall lower attentional state ratings than the highest scoring participant but the lowest scoring participant also fluctuates more in attentional state than the highest scoring participant.

Collectively, these results suggest that pre-trial attentional state ratings strongly predicted subsequent trial performance. When participants rated their current attentional state as highly focused on the current task, performance tended to be high compared to when participants reported their current attentional state as being low and unfocused on the current task. Furthermore, overall attentional state ratings and variability in attentional state ratings (i.e., fluctuations) were moderately correlated with overall levels of performance at an individual level, suggesting that variation in gF is partially due to individual differences in attention control, which is consistent with recent empirical work (Mrazek et al., 2012) and is postulated by a number of recent theories (Kane & Engle, 2002; Unsworth & Engle, 2007).

Table 1
*Descriptive Statistics and Reliability Estimates for Each Experiment*

| Experiment/Measure | *M* | *SD* | Skew | Kurtosis | α |
|---|---|---|---|---|---|
| Experiment 1 | | | | | |
| APM *M* AttnState | 6.82 | 1.69 | −0.29 | −0.20 | .98 |
| APM AttnState *SD* | 1.20 | 0.51 | 0.16 | −0.58 | .66 |
| APM acc | 20.22 | 5.99 | −0.31 | 0.12 | .85 |
| Experiment 2 | | | | | |
| APM *M* AttnState | 7.29 | 1.62 | −0.76 | 0.05 | .99 |
| APM AttnState *SD* | 1.14 | 0.56 | 1.09 | 1.57 | .71 |
| APM acc | 17.12 | 4.66 | −0.58 | −0.07 | .94 |
| Experiment 3 | | | | | |
| LS *M* AttnState | 7.58 | 1.60 | −0.63 | 0.11 | .99 |
| LS AttnState *SD* | 0.89 | 0.51 | 1.40 | 1.80 | .66 |
| LS acc | 8.49 | 2.21 | 0.85 | 1.04 | .73 |
| Voc *M* AttnState | 6.64 | 1.98 | −0.61 | 0.34 | .97 |
| Voc AttnState *SD* | 0.92 | 0.52 | 0.98 | 0.99 | .71 |
| Voc acc | 7.19 | 3.63 | 0.87 | 0.20 | .70 |

*Note*. APM = Raven Advanced Progressive Matrices; *M* AttnState = mean attentional state; AttnState *SD* = standard deviation of attentional state; acc = accuracy; LS = Letter Sets; Voc = Vocabulary.

## Experiment 2

Experiment 1 provided general evidence consistent with the idea that fluctuations in attentional state predict performance on widely used measure of gF. One problem with these results, however, is that item difficulty increased throughout the APM, and attentional state ratings decreased throughout the task. As noted previously, it is possible that the reason pre-trial attentional state predicts subsequent performance might be due to changes in attentional state as a function of problem difficulty. That is, the attentional state ratings are high at the beginning of the task when problems are easy, and as the difficulty increases, participants might lose focus, leading to lower attentional state ratings. Although we tested this notion by examining differences between the first and second halves of the APM, as well as by examining the effect of trial number, a stronger test is needed. Therefore, in Experiment 2, participants performed the same APM task as Experiment 1, but we randomized the problems so that easy and difficult problems were just as likely to come at the end of the task as the beginning. In this way, participants did not know in advance whether the problem would be difficult or easy, and this should provide a better estimate of the predictive utility of pre-trial attentional state ratings.

### Method

Participants were 57 undergraduate students recruited from the subject pool at the University of Oregon. Participants were between 18 and 35 years of age and received course credit for their participation. Each participant was tested individually in a laboratory session lasting approximately 1 hr. All participants performed

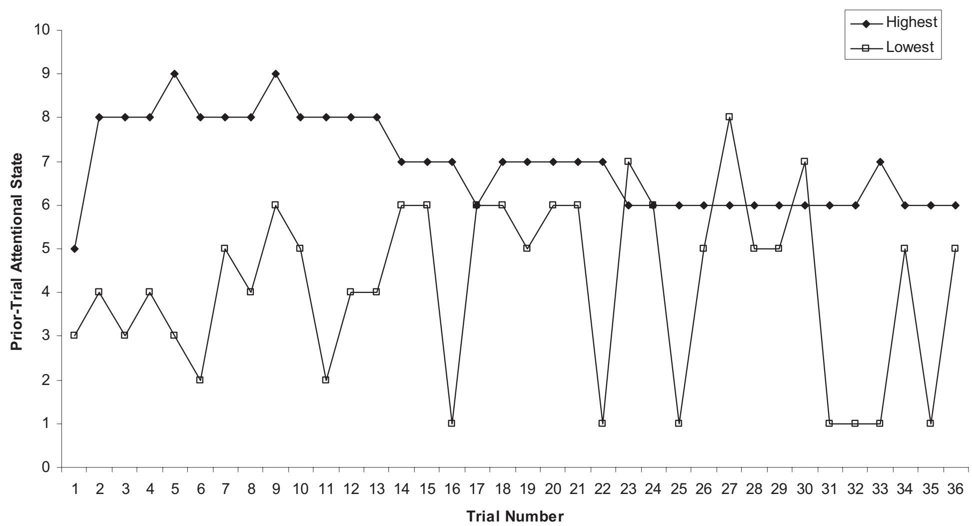


*Figure 4.* Pre-trial attentional state ratings as a function of trial number for the highest and lowest scoring participants in Experiment 1.



the same computerized version of Set II of the APM as in Experiment 1, with the exception that in this version the presentation of the problems was randomized. We initially randomized the presentation of the trial numbers, and each participant performed the same randomized order.[1]

## Results and Discussion

We first examined whether there was a relation between pre-trial attentional state and accuracy on the Raven problems. We used linear mixed models to analyze the data with attentional state entered as a fixed factor and subjects entered as random factors. As shown in Figure 5a, there was a linear effect of attentional state on accuracy, $t = 2.60$, $p < .01$ ($b = .02$, $SE = .01$). This result replicates and extends Experiment 1, suggesting that pre-trial attentional state predicts accuracy on individual APM problems even when the problem order is randomized.

Similar to Experiment 1, we also examined attentional state ratings as a function of trial number. As shown in Figure 5b, attentional state ratings decreased throughout the task, $t = -13.5$, $p < .01$ ($b = -.04$, $SE = .01$). Therefore, similar to Experiment 1, we examined whether trial number would have an effect on accuracy and whether it would interact with attentional state. Entering trial number as a fixed factor in the linear mixed model suggested that there was an effect of attentional state ($b = .02$, $SE = .01$, $t = 2.02$, $p < .05$), but no effect of trial number ($b = .00$, $SE = .01$, $t = .18$, $p > .86$), and no interaction between the two ($t = -.54$, $p > .58$). Thus, randomizing trial number served to equate performance across trials but had no effect on the relation between pre-trial attentional state and accuracy.

Next, we examined whether individual differences in overall attentional state and variability in attentional state would predict performance on the APM. Descriptive statistics are shown in Table 1. Consistent with Experiment 1, there was a moderate positive correlation ($r = .52$, $p < .01$) between participants' attentional states and overall accuracy levels on the APM. There was also a moderate negative correlation ($r = -.27$, $p < .01$) between each individual's standard deviation of attentional state ratings and overall levels of performance. Mean attention state and the standard deviation of attentional state were also correlated ($r = -.48$, $p < .01$). Overall, these results are consistent with Experiment 1, suggesting that pre-trial attentional state ratings predict performance on the subsequent trial, and this occurs even when trials are randomized. Furthermore, similar to Experiment 1, individual differences in attentional state and fluctuations in attentional state are related to individual differences in gF.

# Experiment 3

Experiments 1 and 2 suggested that trial-to-trial fluctuations in attentional state predict trial-to-trial changes in performance on a measure of gF. The purpose of Experiment 3 was to see whether similar results would be found in another measure of gF (Letter Sets) and whether attentional state ratings would predict performance on a measure of gC (vocabulary). As noted previously, one would expect pre-trial attentional state ratings to predict performance on tasks that place heavy demands on focused attention such as gF measures. However, tasks that rely more on basic knowledge retrieval should not demonstrate a relation between attentional state and performance because a participant's current attentional state should not matter much for performance. That is, if you know the definition of a

[1] Note that we have used a version of the APM as used in Experiment 1 and a randomized version of the APM as used in Experiment 2 in prior work and have found both to correlate similarly with a composite measure of working memory capacity (APM-working memory capacity = .34; random APM-working memory capacity = .30). Furthermore, we have used versions of the Letter Sets and vocabulary tasks and have found both to correlate well with other measures of gF (*M* correlation = .45) and gC (*M* correlation = .47), respectively. Thus, although some of the intelligence measures used in the current experiments were somewhat nonstandard, they all have demonstrated construct validity.

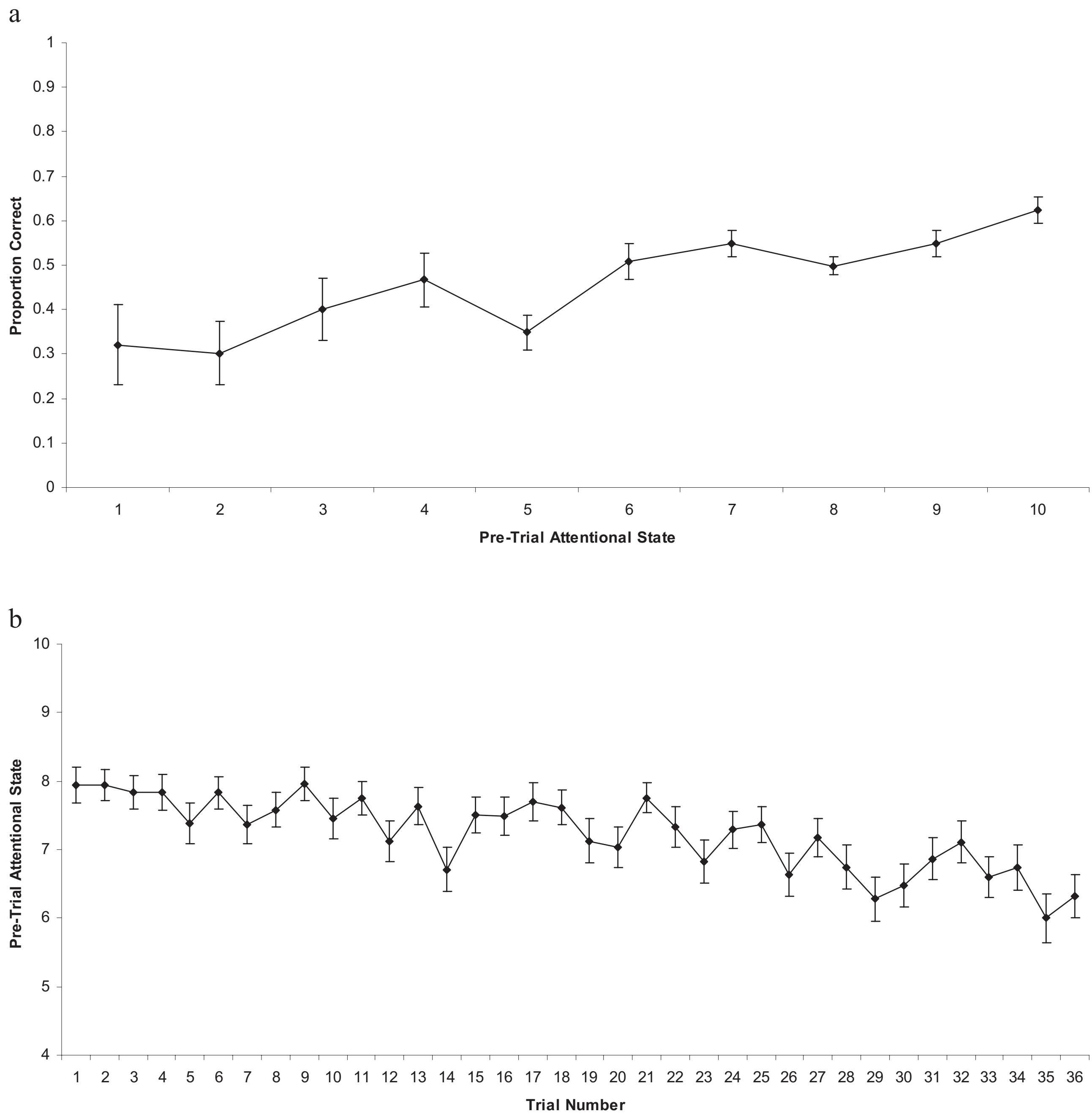


*Figure 5.* (a) Mean proportion correct for the Raven as a function of attentional state in the Raven in Experiment 2. (b) Pre-trial attentional state ratings as a function of trial number in Experiment 2. Error bars represent one standard error of the mean.

particular word, it should not matter much how focused you are on the task. You will likely answer correctly regardless of whether you are very focused or not at all focused. Conversely, if you do not know the definition of a particular word, regardless of how focused you are on the task, the definition cannot be retrieved from your semantic knowledge base. Thus, in this experiment, we expected that pre-trial attentional state ratings would predict performance on a measure of gF but not on a measure of gC, thereby demonstrating a dissociation consistent with the context regulation hypothesis (Smallwood, 2013).

## Method

Participants were 63 undergraduate students recruited from the subject pool at the University of Oregon. Participants were between 18 and 35 years of age and received course credit for their participation. Each participant was tested individually in a laboratory session lasting approximately 1 hr. All participants performed a computerized version of the Letter Sets task and a vocabulary measure. The order of tasks was counterbalanced across participants. In the Letter Sets task, participants saw five sets of four letters, and participants were required to induce a rule that applies to the composition and ordering of four of the five letter sets (Ekstrom, French, Harman, & Dermen, 1976). Participants were required to indicate the set that violated the rule. Following two examples, participants had 7 min to complete 20 test items. A participant's score was the total number of items solved correctly. In the vocabulary test, participants were given 20 vocabulary words and were required to select the best synonym or antonym (out of five possible choices) that best matched the target vocabulary word (Hambrick, Salthouse, & Meinz, 1999). On half of the trials, participants were asked to select the best synonym, and on the other half of trials, participants were asked to select the best antonym. Participants were given 7 min to complete the 20 items. A participant's score was the total number of items solved correctly. Prior to each trial on both tasks, participants were required

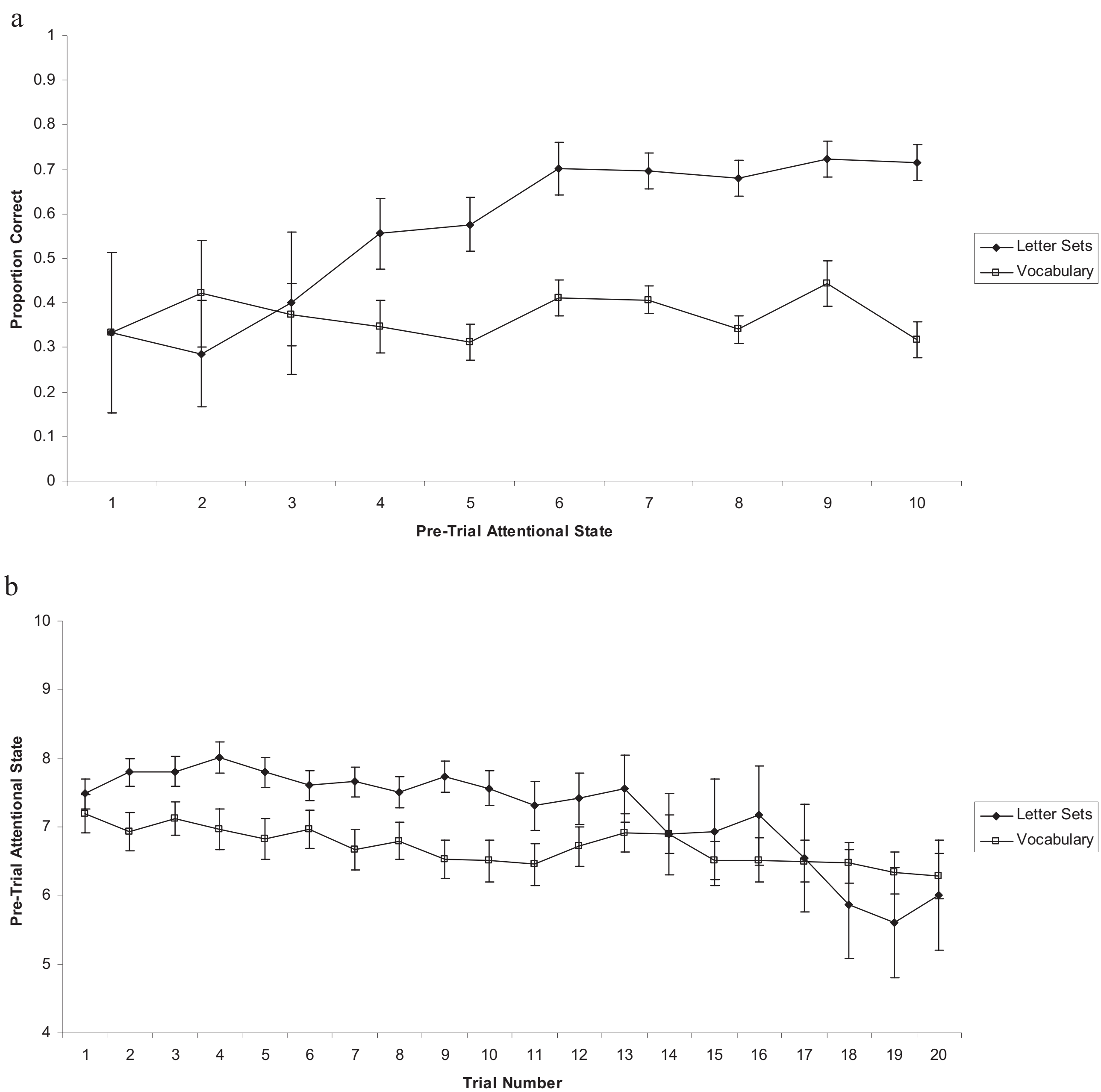


*Figure 6.* (a) Mean proportion correct as a function of task (Letter Sets vs. Vocabulary) and as a function of attentional state in Experiment 3. (b) Pre-trial attentional state ratings as a function of task (Letter Sets vs. Vocabulary) and trial number in Experiment 2. Error bars represent one standard error of the mean.

to indicate their attentional state for the current trial only on a 1–10 scale, with a 1 indicating that they were *not at all focused on the current task*, a 5 indicating that they were *somewhat focused on the current task*, and a 10 indicating that they were *totally focused on the current task*.

## Results and Discussion

First, we examined whether there was a relation between pre-trial attentional state and accuracy as function of the different tasks. We used linear mixed models to analyze the data with attentional state and task (Letter Sets vs. vocabulary) entered as fixed factors and subjects entered as random factors. There was a linear effect of attentional state, $t = 3.09$, $p < .001$ ($b = .06$, $SE = .02$), suggesting that performance decreased as attention state ratings decreased. Importantly, as shown in Figure 6a, there was an interaction between attentional state and task, $t = -2.19$, $p < .05$ ($b = -.02$, $SE = .01$), suggesting that attentional state ratings predicted performance on the Letter Sets but not on the vocabulary task. Indeed, examining each task separately suggested that attentional state predicted performance on the Letter Sets, $t = 3.64$, $p < .001$ ($b = .03$, $SE = .01$), but not on the vocabulary test, $t = 1.42$, $p > .15$ ($b = .01$, $SE = .01$).

Next, we examined attentional state ratings as a function of task and trial number. As shown in Figure 6b, attentional state ratings were higher for the Letter Sets than for vocabulary task, $t = -7.46$, $p < .01$ ($b = -.80$, $SE = .11$), and attentional state ratings decreased throughout the task, $t = -3.60$, $p < .01$ ($b = -.08$, $SE = .02$). However, the interaction between trial number and task did not reach conventional levels of significance, $t = 1.66$, $p > .11$. Therefore, similar to prior experiments, we examined whether trial number would have an effect on accuracy and whether it would interact with attentional state. Entering trial number as a fixed factor in the linear mixed model suggested that there was an effect of trial number ($b = .10$, $SE = .03$, $t = -3.52$, $p < .01$) and an interaction between trial number and task ($b = .05$, $SE = .02$, $t = 3.03$, $p < .01$), suggesting that accuracy tended to decrease more throughout the task for Letter Sets than for vocabulary. Similar to the prior experiments, trial number did not interact with attentional state ($b = .01$, $SE = .02$, $t = 1.43$, $p > .15$), and the three-way interaction between attentional state, task, and trial number was also not significant ($b = -.00$, $SE = .01$, $t = -1.47$, $p > .14$).

For our final set of analyses, we examined whether individual differences in overall attentional state and variability in attentional state would predict performance differentially for the two tasks. Descriptive statistics are shown in Table 1, and the correlations among the measures are shown in Table 2. As can be seen, accuracy on the Letter Sets was correlated with both mean attentional state and each individual's standard deviation of attentional state on the Letter Sets. However, accuracy on the vocabulary test was not related to mean attentional state or the standard deviation of attentional state on the vocabulary test. Note that differences in the correlations are unlikely to be due to differences in task difficulty such that the vocabulary task simply was not as difficult as the Letter Sets. Both tasks demonstrated a similar range of performance across individuals (on Letter Sets, performance ranged from 5 to 15 total items correct, and on vocabulary, performance ranged from 1 to 16 total items correct) and items (in both tasks, accuracy for each item ranged from 0 to 1). If anything, the vocabulary task was slightly more difficult than the Letter Sets. Thus, individual differences in overall attentional state and fluctuations in attentional state predicted performance on a measure of gF but not on a measure of gC. Finally, it worth noting that attentional state ratings (both mean and standard deviation) were correlated across tasks, suggesting that these ratings provide general assessments of attentional state and are not simply task specific.

Table 2
*Correlations Among All Measures in Experiment 3*

| Measure | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. LS *M* AttnState | — | | | | | |
| 2. LS AttnState *SD* | −0.30 | — | | | | |
| 3. LS acc | 0.31 | −0.25 | — | | | |
| 4. Voc *M* AttnState | 0.62 | −0.37 | 0.23 | — | | |
| 5. Voc AttnState *SD* | 0.12 | 0.44 | −0.06 | −0.29 | — | |
| 6. Voc acc | −0.06 | −0.10 | 0.02 | 0.04 | −0.17 | — |

*Note*. Correlations >.24 are significant at the $p < .05$ level. LS = Letter Sets; *M* AttnState = mean attentional state; AttnState *SD* = standard deviation of attentional state; acc = accuracy; Voc = Vocabulary.

## Summary and Conclusions

In the current study, we examined whether trial-to-trial fluctuations in attentional state would predict performance on measures of intelligence. Using a novel attentional probing technique in which participants provided subjective attentional state ratings prior to each trial (Macdonald et al., 2011), we provide direct evidence for the role of attention and fluctuations in attention in determining performance on measures of gF (see also Mrazek et al., 2012). Specifically, the results suggest that pre-trial attentional state ratings strongly predicted subsequent trial performance. When participants rated their current attentional state as highly focused on the current task, performance tended to be high compared to when participants reported their current attentional state as being low and unfocused on the current task. Of course, the direction of causality remains an open question. It is possible that pre-trial attentional state causes differences in performance; it is also possible that gF could be causing differences in attention. Future work is needed to better disentangle issues regarding the direction of causality. Furthermore, overall attentional state ratings and variability in attentional state ratings (i.e., fluctuations) were moderately correlated with overall levels of performance at an individual level, suggesting that variation in gF is partially due to individual differences in attention control, as postulated by a number of recent theories (Kane & Engle, 2002; Unsworth & Engle, 2007). However, trial-to-trial fluctuations in attentional state did not predict performance on a measure of gC, and individual differences in attentional state did not predict variation in vocabulary performance. This dissociation suggests that although fluctuations in attentional state likely arise on all tasks, only tasks that require a great deal of focused and sustained attention will be impacted by these fluctuations. Tasks that rely on more automatic processes or basic knowledge retrieval will not be as impacted by fluctuations in attentional state. Overall, these results are consistent with the context regulation hypothesis, suggesting that fluctuations in attentional state will interfere with tasks that require focused attention but will not influence performance much on tasks that require less focused attention (e.g., Smallwood, 2013). Collectively, the current results suggest that the ability to focus and sustain attention on task (as revealed by attentional state ratings) is an important contributor to performance on measures of gF. Future work is needed to better examine how fluctuations in attention are related to other important contributors to gF. By measuring subjective attentional state on a trial-to-trial basis, the current results provide a promising means for examining fluctuations in attention and their role in complex higher order cognitive operations like gF.

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