Attentional resource allocation among individuals with different fluid intelligence: The integrated control hypothesis and its evidence from pupillometry

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Abstract

To clarify the effects of individual differences in fluid intelligence (Gf) on attentional resource allocation, the present study proposes a new hypothesis (i.e., the integrated control hypothesis) based on previous studies and provides preliminary empirical evidence through a pupillometry study. The results showed that both task type and task difficulty play crucial roles in the relationship between Gf and attentional resource allocation. In particular, in the exploitation task, higher Gf individuals allocated fewer attentional resources than those with average Gf at all the difficulty levels. In contrast, in the exploration task, those with higher intelligence allocated equivalent resources in the low- and medium-difficulty trials and more resources in the high-difficulty trials; this phenomenon was more significant among the male subjects. In conclusion, this study suggests that high Gf individuals tend to control their attention state in tasks with diverse demands, allowing them to dynamically optimize the use of attentional resources and flexibly adapt to changing conditions.

Key words: attentional resource allocation; fluid intelligence; individual differences; integrated control hypothesis; pupillometry

1. Introduction

According to the *capacity theory for attention* (Kahneman, 1973), attentional resources (also known as mental effort, processing resources or cognitive resources) refer to the amount of available activation for information storing and processing (Just, Carpenter, & Miyake, 2003; van der Meer et al., 2010). Although the capacity of attentional resources is assumed to be limited and dependent on the structures and functions of the neural system (Just, Carpenter, & Miyake, 2003), people can allocate their resources with considerable freedom among concurrent activities according to their allocation policy (Kahneman, 1973). In addition to task demands, enduring dispositions and momentary intentions, which were proposed in Kahneman's original model (1973), researchers have proposed that individual differences in fluid intelligence (Gf) also play an indispensable role in resource allocation policy (e.g., Ahern & Beatty, 1979; van der Meer et al., 2010). In addition to having more potential resources, people with high Gf are assumed to flexibly control their attention state according to changing conditions (Rueda, 2018), allowing them to adopt different resource allocation policies in diverse tasks. Moreover, early cognitive neuroscience studies have found that people with different levels of intelligence have different patterns of brain activity while solving cognitive tasks, providing preliminary empirical evidence of the potential role of Gf (e.g., Haier et al., 1988). Therefore, it is necessary to clarify the effects of individual differences in Gf on attentional resource allocation with empirical studies to further understand the cognitive processes of high Gf people and the nature of Gf.

To objectively and dynamically measure participants' resource allocation, researchers have found several effective methods (Just, Carpenter, & Miyake, 2003); the most common indicator is a *task-evoked pupillary response* (TEPR; Ahern & Beatty, 1979; Hayes, & Petrov, 2016; van der Meer et al., 2010). Numerous studies have found that the more attentional resources required to complete a cognitive task, the greater the pupil dilation evoked by the task (Alnaes, Sneve, Espeseth, Endestad, van de Pavert, & Laeng, 2014; Belayachi, Majerus, Gendolla, Salmon, Peters, & Van der Linden, 2015; Klingner, Tversky, & Hanrahan, 2011; van der Meer et al., 2010); this pupillary response is not related to particular tasks (see the review by Eckstein, Guerra-Carrillo, Miller Singley, & Bunge, 2017; van der Wel & van Steenbergen, 2018). Moreover, by scrutinizing many previous studies, van der Wel and van Steenbergen (2018) explained that the TEPR is actually induced by internal mental effort (similar to the concept of resource allocation) rather than external task difficulty.

The neural basis of pupil dilation reflecting resource allocation has been explored in recent years. Neuroscience studies at various levels, such as single-cell recordings (Rajkowski, Kubiak, & Aston-Jones, 1993; Joshi, Li, Kalwani, & Gold, 2016), pharmacology (Phillips, Szabadi, & Bradshaw, 2000), electrophysiology (Murphy, Robertson, Balsters, & O'Connell, 2011) and functional magnetic resonance imaging (fMRI; Alnaes et al., 2014; Murphy, O'Connell, O'Sullivan, Robertson, & Balsters, 2014), have found a strong correlation between the pupil response and activity in the locus coeruleus (LC), which is a subcortical structure located on each side of the rostral pons in the brainstem that serves as the sole source of norepinephrine (NE), rendering the pupillary response a non-invasive index that indirectly reflects the activity of the LC-NE system (Laeng, Sirois, & Gredeback, 2012). Since the LC-NE system regulates the functioning of the brain's attention system (Aston-Jones & Cohen, 2005; Petersen & Posner, 2012), the pupil response reflects attentional resource allocation while completing cognitive tasks.

To date, at least the following three different hypotheses regarding the relationship between Gf and resource allocation have been proposed: the *efficiency hypothesis* (Ahern & Beatty, 1979), the *resource hypothesis* (van Der Meer et al., 2010), and the *control hypothesis* (Hayes, & Petrov, 2016). The efficiency hypothesis (see Figure 1A) suggests that compared with those with average Gf, high Gf individuals have higher neural functional efficiency and use fewer resources in cognitive tasks regardless of the difficulty; this hypothesis is similar to the influential neural efficiency hypothesis (Haier et al., 1988). Ahern and Beatty's study (1979) found that high Gf individuals had a smaller TEPR (i.e., allocated fewer resources) when they completed mental arithmetic problems of all difficulty levels, supporting the efficiency hypothesis, as the highly intelligent people required fewer attentional resources to solve problems due to their higher efficiency. Furthermore, a recent pupillometry study (Lee et al., 2015) found similar results, supporting the efficiency hypothesis in arithmetic problems.

However, many studies have found that the efficiency hypothesis could not explain all empirical results. Researchers suggested that other factors, such as task difficulty, task type, and gender, may also influence this relationship (Neubauer & Fink, 2009). For example, van der Meer et al. (2010) required participants with different Gf to complete a graphic symmetry task with various difficulty levels. Interestingly, the high Gf individuals showed a greater TEPR while performing the difficult graphic symmetry task than the average Gf individuals, while there were no significant differences in the TEPRs between the two groups in the simple graphic symmetry task. Based on these results, van der Meer et al. (2010) proposed a new theory called the resource hypothesis, which posits that the relationship between Gf and resource allocation is influenced by task difficulty (Figure 1B). Specifically, when the task difficulty is low, both high and average Gf individuals can easily solve the tasks, and high Gf individuals show a TEPR smaller than or nearly equal to that of average Gf individuals. In contrast, in high-difficulty tasks, high Gf people show a larger TEPR than average Gf individuals since they devote more attentional resources to solve the problems. Subsequently, Bornemann et al. (2010) also found similar results supporting the resource hypothesis using a graphic symmetry task. However, this study did not find significant differences between high and average Gf individuals in arithmetic tasks, indicating the possibility that the task type plays a critical role.

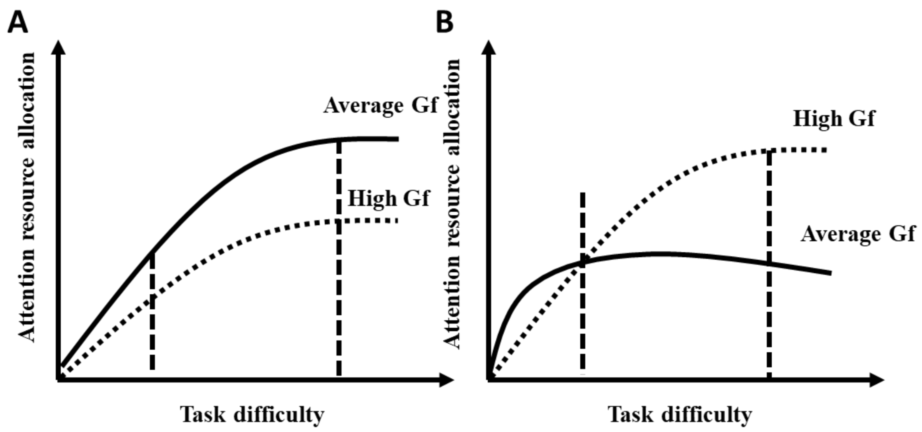


Figure 1 Illustrations of the (A) efficiency hypothesis and (B) resource hypothesis

We observed that studies supporting the efficiency hypothesis or resource hypothesis often used different types of tasks. Specifically, the studies supporting the efficiency hypothesis often adopted arithmetic tasks, while those supporting the resource hypothesis tended to use explorative tasks, such as graphic symmetry tasks. A recent study used both arithmetic and similar visuospatial explorative tasks to further verify the conjecture that the task type may play a crucial role in the relationship between Gf and resource allocation (Lee et al., 2015). These authors found that the results of the linguistic reasoning task and visuospatial mental folding task supported the resource hypothesis, while the results of the arithmetic task supported the efficiency hypothesis. Subsequently, Hayes and Petrov (2016) used concurrent think-aloud verbal protocols to distinguish participants' cognitive states (i.e., exploration and exploitation) while completing Raven's Advanced Progressive Matrices (RAPM) with their TEPRs recorded. Exploration and exploitation are two control states critical for optimizing behavioural performance and are important for understanding executive control (Cohen, McClure, & Yu, 2007). Both exploration and exploitation states can be involved to varying degrees in specific tasks. Tasks mainly involving the exploration state require a search of an abstract or unfamiliar problem space to forage potential relationships, while tasks mainly involving the exploitation state require the utilization of known relationships to solve problems (Hayes & Petrov, 2016). Previous studies have found that the exploration-exploitation trade-off may be regulated by the LC-NE system (Aston-Jones & Cohen, 2005; Jepma & Nieuwenhuis, 2011). Hayes and Petrov (2016) found that the high Gf participants had a significantly large TEPR during the exploration period and a relatively small TEPR during the exploitation period.

Furthermore, the authors proposed the control hypothesis, which posits that the task type affects the relationship between Gf and resource allocation. In particular, in tasks mainly requiring the exploration state (referred to as exploration tasks), such as graphic symmetry tasks (Bornemann et al., 2010; van der Meer et al., 2010) or mental folding tasks (Lee et al., 2015), those with higher intelligence exert more attentional resources than average Gf individuals because they tend to shift into a higher-gain state. In contrast, in tasks mainly requiring the exploitation state (referred to as exploitation tasks), such as arithmetic problems (Ahern & Beatty, 1979; Lee et al., 2015), high Gf people use fewer resources due to their higher efficiency.

Although the control hypothesis offers an original and reasonable explanation for previous conflicting findings, several questions remain to be further explored. First, this study distinguished exploration and exploitation states in one task (i.e., RAPM), which was also used as a scale to measure the participants' Gf. According to the results of the think-aloud verbal protocols, RAPM could be considered an integrated task with similar exploration and exploitation requirements (with 990 exploration features and 945 exploitation features in the verbal protocols; Hayes & Petrov, 2016). Whether participants' TEPRs in two independent tasks that mainly involve exploration or exploitation conform to the control hypothesis should be verified. In addition, the control hypothesis does not emphasize the effect of task difficulty in the two tasks because RAPM is relatively highly difficult. According to the literature review mentioned above, we found that both task type and task difficulty may play important roles in the relationship between Gf and attentional resource allocation and both should be considered from the perspective of integration.

Based on the results reviewed above, we propose the following new hypothesis: the integrated control hypothesis (Figure 2). This new hypothesis suggests that both task type and task difficulty can influence the relationship between Gf and resource allocation. In particular, in exploitation tasks (such as arithmetic problems), task difficulty may not influence this relationship, as high Gf people use fewer resources to efficiently resolve tasks in tasks of all difficulties, supporting the efficiency hypothesis (Ahern & Beatty, 1979; Lee et al., 2015). In contrast, in tasks mainly involving exploration (such as graphic symmetry tasks and mental folding tasks requiring constant exploration of the problem space), task difficulty may influence the relationship such that compared with average Gf individuals, high Gf individuals allocate more resources for difficult tasks and fewer or nearly equal resources for easy tasks, supporting the resource hypothesis. As shown in Figure 2, the integrated control hypothesis provides a more compatible model explaining the relationship between Gf and resource allocation and can explain most previous contradictory results.

Theoretically, the integrated control hypothesis emphasizes that high Gf individuals have a better ability of attention control that can flexibly allocate their attentional resources according to specific task types and task demands. In view of the integrated control hypothesis, the efficiency of high Gf people does not simply present as using fewer resources to solve problems but is reflected in their flexibility and rapid adaptation to changing conditions (Dunst et al., 2014; Rueda, 2018), which maximizes resource utilization across different tasks. In exploitation tasks requiring participants to only utilize familiar rules to solve the problems, high Gf participants tend to adopt an economical resource allocation policy. In contrast, in exploration tasks requiring constant effort in the problem space, high Gf individuals are inclined to allocate more resources in difficult trials to solve the problems but invest fewer resources in simple trials.

In addition, as mentioned above, many researchers have also found a significant role of gender in the relationship between Gf and resource allocation (Dunst et al., 2014; Grabner, Fink, Stipacek, Neuper, & Neubauer, 2004; Neubauer et al., 2002). For instance, an EEG study (Grabner et al., 2004) found that only male participants showed a pattern supporting the neural efficiency hypothesis under the experimental conditions, while females did not present this significant pattern. Furthermore, researchers found that the effect of gender may have an interaction with task type and that participants of both genders show neural efficiency in the domain where they often perform better (Neubauer, Grabner, Fink, & Neuper, 2005). Therefore, we also evaluated the role of gender in this study considering the potential interaction between gender and other variables.

In summary, the present study aimed to examine the newly proposed integrated control hypothesis focusing on both effects of task type and task difficulty on the relationship between Gf and attentional resource allocation based on empirical pupillometry evidence. In addition, we also preliminarily examined the potential role of gender in this relationship.

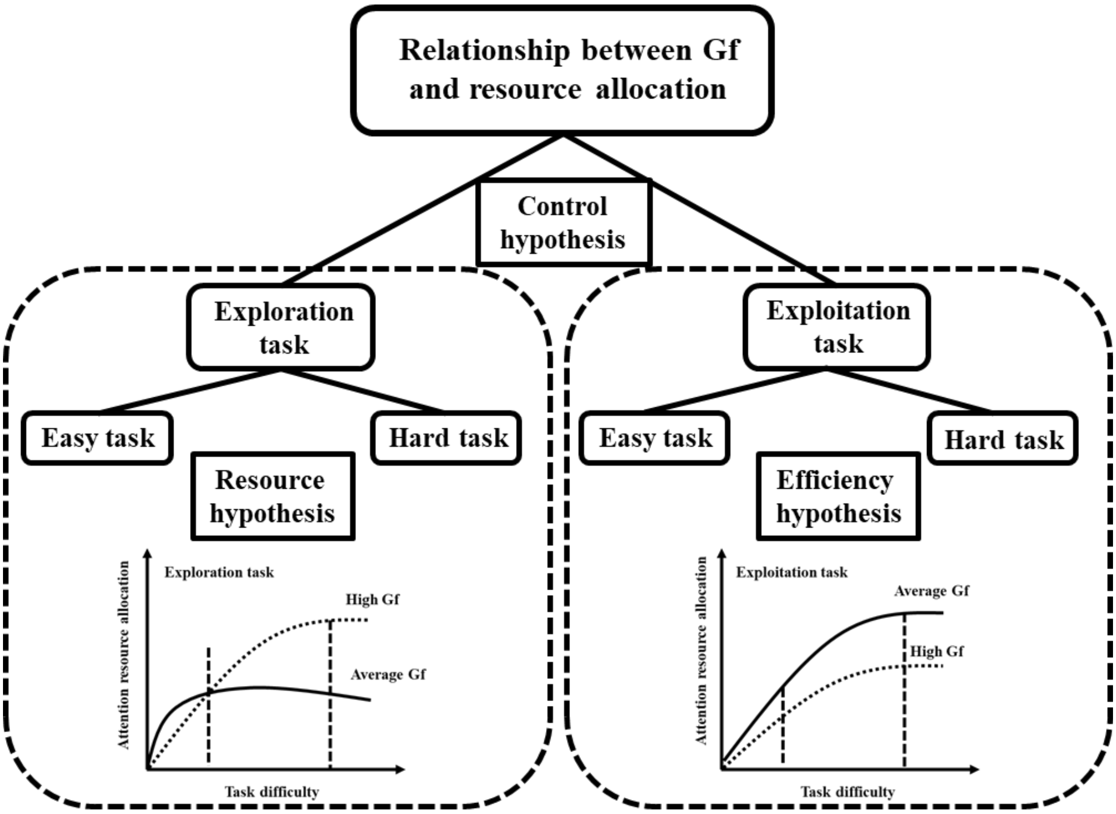


Figure 2 Integrated control hypothesis: The relationship between fluid intelligence (Gf) and attentional resource allocation is influenced by both task type (as proposed by the control hypothesis; Hayes and Petrov, 2016) and task difficulty. In the exploration task, high Gf individuals allocate more attentional resources than average Gf individuals when task difficulty is high but allocate equivalent attentional resources when task difficulty is low, which echoes the previous resource hypothesis (e.g., van der Meer et al., 2010). In the exploitation task, by contrast, high Gf individuals allocate fewer attentional resources across all task difficulties, in consistent of the efficient hypothesis (e.g., Ahern and Beatty, 1979).

2. Methods

2.1 Participants

We used G*Power (Faul et al., 2008) to conduct a statistical power analysis with power (1-β) set at 0.9 and $\alpha = 0.05$ to determine the required sample size. The results showed that at least 36 participants are required to detect a two-way interaction effect (Gf group × task difficulty) with a medium effect size (effect size $f = 0.25$). We finally recruited 65 participants from local universities for the present study; three participants were excluded from the analyses because they did not complete all tasks as required. The remaining 62 participants (26 men and 36 women) with a mean age of 22.47 years (*SD* = 2.41) were right-handed and had normal or corrected-to-normal vision without astigmatism. In addition, none of the participants had a history of psychiatric disease or were taking medication.

2.2 Tasks, apparatus and procedures

2.2.1 Measurement of fluid intelligence

We used RAPM (Raven, 1958) in the paper-and-pencil form to evaluate the participants' Gf. The participants were required to complete this 36-item test in 40 minutes, and the final Gf score was calculated as the number of correct items, since each item was assigned one point. The obtained RAPM scores showed adequate Cronbach's α values (0.73), indicating good reliability in this sample.

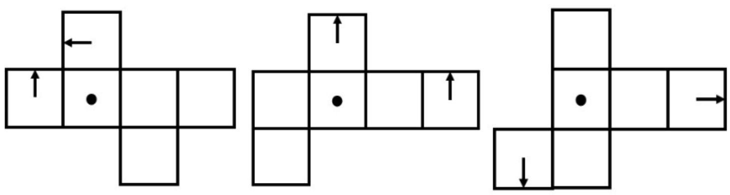
All participants were divided into two groups according to the mean Gf score (26.87). Individuals scoring over 26.87 were assigned to the high Gf group ($N = 32$, $M_{Gf} = 29.94$, $SD = 2.30$), and individuals scoring below 26.87 were assigned to the average Gf group ($N = 30$, $M_{Gf} = 23.60$, $SD = 2.87$). The Gf scores significantly differed between the two groups [$t(60) = 9.62$, $p < 0.001$].

2.2.2 Exploration task

We utilized a mental paper folding task (Shepard & Feng, 1972) as the exploration task (Figure 3). The stimuli of this task consist of six squares joined together representing an unfolded cube, with a black dot presented in one of the squares as the base of the cube and two arrows pointing to one of the sides of particular squares. The participants were required to mentally fold this two-dimensional pattern into a three-dimensional cube using the surface with the black spots as the base and then judge whether the two edges indicated by the two arrows could overlap after folding. In this study, half of the stimuli were ‘match’ trials, and the other half were ‘mismatch’ trials. Previous studies have suggested that the mental folding task can force subjects to fold one surface at a time (Sun & Feng, 2016), and subjects have to perform psychological operations step-by-step each time without applying any rules, meeting the requirements of exploratory tasks. In addition, we also interviewed 45 participants towards their thoughts when they performed this task using two questions (Q1: You tend to use some rules that you already know to answer these questions; Q2: You cannot be sure of its rules, and you have to keep exploring in order to answering it), and asked them to evaluate how correct the two expressions are from 0 (completely disagree) to 100 (completely agree). The results showed that the mean scores of these two questions are 29.15 and 77.78, indicating this task is a typical task involving more exploration. In addition, from the interview we also noticed that the low-difficulty trails in the exploration task may show fewer exploratory features because they were too easy, while medium- and high-difficulty trials exactly showed exploratory features.

According to previous studies (Milivojevic, Johnson, Hamm, & Corballis, 2003; Shepard & Feng, 1972), the difficulty level of this task was classified by the total number of squares involved in the match-mismatch decision (see Shepard & Feng, 1972 for more detail). As shown in Figure 3, the low-, medium-, and high-difficulty problems involved folding two, four and six squares, respectively. Prior to the formal experiment, the participants completed six practice items to become familiar with the procedure and were provided feedback regarding the correctness of their answers after each trial. The formal experiment consisted of 120 trials (40 trials per difficulty level) divided into 5 blocks, and each block included 24 trials presented in a Latin square order.

Each trial included five phases (Figure 4) starting with a fixation cross presented for 2000 ms, and the mean pupil size in the last 200 ms was calculated as the baseline pupil size (fixation phase). Then, the stimuli were presented on the screen (stimulus presentation phase), and the subjects were required to press the space key to progress to the answering phase (the maximum duration was 30 s) once they reached their answers. The participants' pupil sizes were recorded during this stimulus presentation phase to calculate the TEPR. After the answer (yes/no) was entered, a mask with the same luminance as the test items was presented for 1000 ms to allow the pupil size to return to its baseline state (mask phase), followed by a smiley face on the screen indicating that the subjects were allowed to start the next trial by pressing the space key (relaxation phase). During each trial, the participants were required to not move their head or body, except for during the relaxation phase.



Two squares involved **Four squares involved** **Six squares involved**

Figure 3 Examples of the stimuli of the mental paper folding tasks with different difficulty levels (low-, medium-, and high-difficulty trials from left to right)

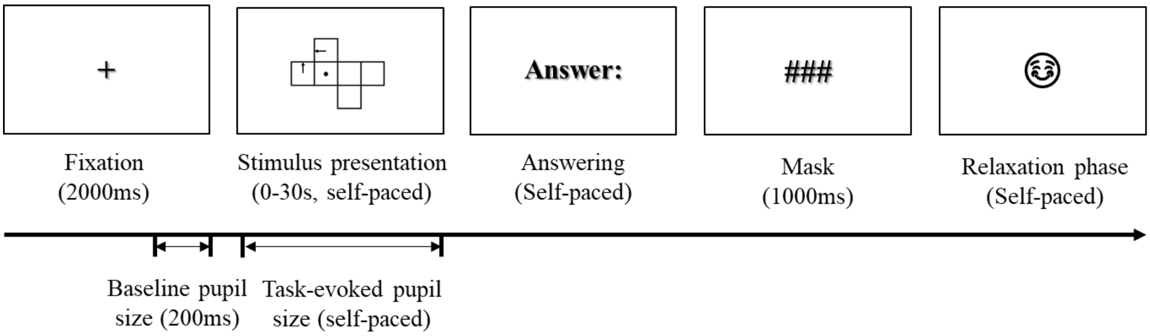
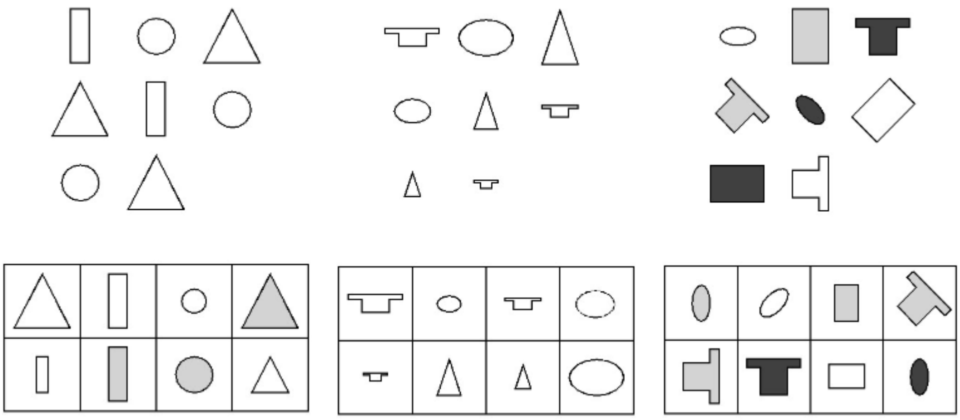


Figure 4 Illustrations of the five phases in each trial in the exploration task

2.2.3 Exploitation task

We used matrix completion tasks with limited rules generated by a software program (Matzen, Benz, Dixon, Posey, Kroger, & Speed, 2010) as the exploitation task. Although this task involved a reasoning process, we only chose questions with limited attributes in this task. Moreover, these limited attributes were completely taught to the participants during the practice session to allow them to utilize these rules to directly solve the tasks, which met the requirements of exploitation tasks. In addition, after the whole study, we also interviewed 45 participants towards their thoughts when they performed this task using two questions (Q1: You tend to use some rules that you already know to answer the questions; Q2: You cannot be sure of its rules, and you have to keep exploring in order to answering it), and asked them to evaluate how correct the two expressions are from 0 (completely disagree) to 100 (completely agree). The results showed that the mean scores of these two questions are 85.4 and 32.82, indicating this task is a typical task involving more exploitation. Further interview results indicated that all three difficulty levels showed the exploitative features. Notably, although this task is similar to RAPM in form, the two tasks have different natures because participants have been familiar with all the rules during the practice period in the present task. We also asked participants to answer the two same questions towards RAPM, and the results of the two scores are 50.69 and 48.46, indicating that RAPM is a more balanced task involving both exploration and exploitation.

According to the number of attributes required to be considered, as shown in Figure 5, the stimuli were divided into three difficulty levels with the low-, medium-, and high-difficulty trials involving one, two, and three attributes to be considered, respectively. Prior to the formal experiment, the participants completed eight practice items to become fully familiar with the procedure and the limited rules of the task and were provided feedback regarding the correctness of their answers after each trial. The formal experiment also consisted of 120 trials (40 trials per difficulty level) divided into 5 blocks, and each block included 24 trials presented in a Latin square order. The experimental phases of each trial and the time interval during which the participants' pupil sizes were recorded were the same as those in the exploration task (Figure 4), except that the stimuli were changed in the exploitation tasks.



One attribute involved **Two attributes involved** **Three attributes involved**

Figure 5 Examples of the stimuli of the matrix completion tasks with different difficulty levels (low-, medium-, and high-difficulty trials from left to right)

2.3 Apparatus

We recorded the participants' TEPRs using a Tobii T60XL eye tracker (Tobii Technology, Stockholm, Sweden) sampling at 60 Hz. The participants were seated at a distance of approximately 60 cm from a 24-in monitor with a resolution of 1920 × 1200 pixels. All participants completed the whole eye-tracking experiment in the same windowless room at a constant slightly dimmed illumination level. The pupillometry experiments were controlled with the E-prime extension for Tobii. A five-point calibration procedure was conducted by each participant prior to the start of the formal experiment.

2.4 Procedures

The participants were tested individually in the same windowless room after completing an informed consent form. First, two sessions of the eye-tracking experiment were conducted, with half of the participants starting with the exploration task and the other half beginning with the exploitation task. After the eye-tracking experiment and a five-minute break, the participants completed RAPM in 40 minutes. After the entire experiment was completed, the participants were paid for participating in this research. All experiments reported in this study were approved by the Ethical Review Board of the Institute of Psychology, Chinese Academy of Sciences.

2.5 Data analysis

First, incorrect responses were excluded from the data analyses. After visually inspecting the data quality, the pupillary data (only data from the left eye were used due to the extremely high correlation between the pupil sizes of both eyes) were preprocessed using the R package *pupilParse* (R Core Team, 2018; scripts are available at https://github.com/thohag/pupilParse). All raw data were subjected to all preprocessing procedures, including linear interpolation, Hampel filtering (Pearson, 1999) and Lowess smoothing (Cleveland, 1981), to replace artefacts and time intervals containing blinks and exclude outliers and high-frequency noises (Aminihajibashi et al., 2019). After preprocessing the raw pupillary data, the pre-trial baseline pupil size was calculated by the mean pupil size during the 200 ms before the stimulus presentation. In addition, the mean TEPR (calculated as the mean task-evoked diameter during the stimulus presentation phase minus the mean baseline diameter) was calculated by R as an index of attentional resource allocation. Before the statistical analyses, participants with an accuracy lower than 0.8 in one task were excluded from further analyses of this task (three participants in the exploration task and four participants in the exploitation task). Therefore, 58 participants (32 high Gf participants) were involved in the analyses of the exploitation task while 59 participants (30 high Gf participants) were finally involved in the analyses of exploration task. In the analyses involving gender, 32 high Gf (17 males and 15 females) and 26 average Gf (7 males and 19 females) individuals were included in the analysis of the exploitation task, and 30 high Gf (15 males and 15 females) and 29 average Gf (8 males and 21 females) individuals were included in the analysis of the exploration task. The descriptive and inferential statistical analyses were conducted with JASP (v.0.11.1.0).

3. Results

3.1 Behavioural results

We conducted two 2 (Gf group: high vs. average) × 3 (task difficulty: low vs. medium vs. high) repeated-measures ANOVAs in each task to examine the differences in task performances after calculating the mean and standard deviation of the behavioural results (Table 1).

In the exploration task, the main effects of both task difficulty [F (2,114) = 94.36, $p < 0.001$, $\eta_p^2 = 0.62$] and Gf group [F (1,57) = 3.47, $p = 0.07$, $\eta_p^2 = 0.06$] on accuracy were significant or marginally significant. In specific, participants' accuracy tended to be lower when task became harder and high Gf participants had relatively higher accuracy than average Gf participants. No interaction between Gf and task difficulty was found [F (2,114) = 2.19, $p = 0.12$, $\eta_p^2 = 0.04$]. Regarding the reaction time (RT) results, we only found a significant main effect of task difficulty [F (2,114) = 458.43, $p < 0.001$, $\eta_p^2 = 0.89$] on it. Neither the main effect of Gf [F (1,57) = 1.72, $p = 0.19$, $\eta_p^2 = 0.03$] nor the interaction between Gf and task difficulty [F (2,114) = 0.54, $p = 0.58$, $\eta_p^2 = 0.01$] reached significant level.

In the exploitation task, we found a significant interaction between Gf group and task difficulty on accuracy [F (2,112) = 9.30, $p < 0.001$, $\eta_p^2 = 0.14$]. Simple effect analysis showed that high Gf participants showed significantly higher accuracy in both medium- [F (1,114) = 4.97, $p = 0.03$] and high-difficulty [F (1,114) = 14.19, $p < 0.001$] conditions than average Gf participants but not in the low-difficulty condition [F (1,114) = 0.01, $p = 0.94$]. Similarly, there was also a significant interaction between Gf group and task difficulty on RT [F (2,112) = 6.74, $p = 0.002$, $\eta_p^2 = 0.11$]. Average Gf participants showed longer RT than high Gf participants in low- [F (1,112) = 5.53, p =

0.02] and medium-difficulty [F (1,114) = 8.08, p = 0.006] conditions but not in high-difficulty condition [F (1,114) = 0.01, p = 0.94].

We additionally checked the potential role of gender in accuracy and gender by using a 2 (gender: male vs. female) × 2 (Gf group: high vs. average) × 3 (task difficulty: low vs. medium vs. high) repeated-measures ANOVA in each task. We found a significant interaction between Gf group, gender, and task difficulty in accuracy of the exploitation task. Further simple effect analysis found that only in the high-difficulty condition of the exploration task, high Gf male participants showed significantly higher accuracy than average Gf male participants [F (1,108) = 27.20, p < 0.001]. No other main effects or interaction effects involving gender was found in the behavioural data.

3.2 TEPR results

After calculating the mean and standard deviation of TEPR (Table 1), we conducted two 2 (Gf group: high vs. average) × 3 (task difficulty: low vs. medium vs. high) repeated-measures ANOVAs taking TEPR as dependent variable in each task to examine the roles of Gf and task difficulty in them. Furthermore, the pupillary time-domain waveforms in both tasks were shown in Figure S1.

3.2.1 Exploitation task

The pupillary results showed that the interaction between Gf group and task difficulty are not significant in the exploitation task [F (2,112) = 0.63, p = 0.03, η_p^2 = 0.01]. However, we found both main effects of task difficulty [F (2,112) = 28.66, p < 0.001, η_p^2 = 0.34] and Gf group [F (1, 56) = 5.98, p = 0.02, η_p^2 = 0.10]. Specifically, participants with higher Gf showed smaller TEPR than participants with average Gf in all three difficulty levels, although both groups of participants showed larger TEPR in more difficulty conditions (Figure 6A). The temporal waveforms of TEPR (Figure S1) suggested that high Gf participants showed smaller TEPR throughout the time course. In addition, we also conducted Pearson's correlation between Gf and TEPR as a supplementary analysis and the results indicated that Gf had a trend to be negatively correlated with TEPR in all three difficulty levels (r = -0.24, p = 0.071; r = -0.25, p = 0.056; r = -0.25, p = 0.063, respectively; Figure S2). Noting that there was an outlier (Gf = 12) in this dataset which might influence the results of correlation analyses, we also performed another set of correlation analyses without this outlier. The results showed that the trends between Gf and TEPR were still negative after removing that single participant (r = -0.23, p = 0.09; r = -0.27, p = 0.04; r = -0.24, p = 0.08, respectively; Figure S3).

To examine the role of gender in this relationship, we performed a 2 (gender: male vs. female) × 2 (Gf group: high vs. average) × 3 (task difficulty: low vs. medium vs. high) repeated-measures ANOVA in the exploitation task. The results showed that in the exploitation task, there were no significant interaction effects with gender, and the main effect of gender was significant [F (1,54) = 16.95, p < 0.001, η_p^2 = 0.24], with the female participants' TEPR being significantly higher than that of the male participants.

3.2.2 Exploration task

Similarly, we found a strong main effect of task difficulty on TEPR in the exploration task [F (2,114) = 153.28, p < 0.001, η_p^2 = 0.73]. As the task became more difficult, participants tended to show larger TEPR. Although we did not find a significant main effect of Gf [F (1,57) = 0.03, p = 0.86, η_p^2 = 0.001], the interaction between Gf group and task difficulty was marginally significant in the exploration task [F (2,114) = 3.09, p = 0.05, η_p^2 = 0.05]. There was a trend that higher Gf participants showed smaller TEPR in the low-difficulty condition but larger TEPR in the high-difficulty condition, although the simple effect analysis did not find any significant differences between the two Gf groups in all three difficulty levels (all ps > 0.37). Correlation analyses also did not find any significant correlations between Gf and TEPR in the exploration task (all ps > 0.36).

However, we found a significant three-way interaction effect among gender, Gf group and task difficulty in the exploration task [F (2,110) = 6.78, p = 0.002, η_p^2 = 0.11]. An additional simple effect analysis showed that the TEPR of the male participants with high Gf was significantly higher than that of the male participants with average Gf [F (1,110) = 5.96, p = 0.02] in the high-difficulty trials, while this phenomenon was absent in the female participants (Figure 7). We further examined the correlations between Gf and TEPRs in different genders in the exploration task. The results showed that with the task difficulty increasing, the correlations between Gf and TEPRs in male participants turned from negative to positive (r = -0.15; r = -0.05; r = 0.21; respectively; Figure S4), although these correlation coefficients did not reach a significant level (ps > 0.1). In contrast, these correlations in female participants remained negative in all three difficulty levels, no matter include or exclude the outlier (Figure S5).

Table 1 Means and standard deviations (in brackets) of behavioural results and TEPR in the exploitation task and the exploration task with different difficulty levels

Task type	Difficulty	RT (s)		Accuracy (%)		TEPR (mm)	
		H-Gf	A-Gf	H-Gf	A-Gf	H-Gf	A-Gf

Exploitation ($N_{H\text{-}Gf}$ = 32, $N_{A\text{-}Gf}$ = 26)	Low-difficulty	6.32 (1.13)	7.25 (1.86)	98.12 (2.29)	98.17 (2.79)	0.15 (0.10)	0.22 (0.10)
	Medium-difficulty	9.59 (1.37)	10.78 (1.82)	91.33 (5.20)	87.98 (6.25)	0.20 (0.12)	0.27 (0.13)
	High-difficulty	13.83 (1.90)	13.79 (1.69)	79.69 (7.15)	72.21 (7.95)	0.20 (0.13)	0.29 (0.15)
Exploration ($N_{H\text{-}Gf}$ = 30, $N_{A\text{-}Gf}$ = 29)	Low-difficulty	2.26 (0.66)	2.86 (0.96)	98.33 (2.40)	98.19 (2.40)	0.16 (0.09)	0.18 (0.09)
	Medium-difficulty	5.28 (1.71)	5.93 (1.73)	96.08 (4.29)	94.48 (4.19)	0.28 (0.10)	0.27 (0.12)
	High-difficulty	8.83 (2.33)	9.08 (2.28)	87.42 (10.76)	83.19 (7.19)	0.37 (0.15)	0.34 (0.14)

Note: RT, reaction time; TEPR, task-evoked pupillary response; H-Gf, high fluid intelligence participants; A-Gf, average fluid intelligence participants

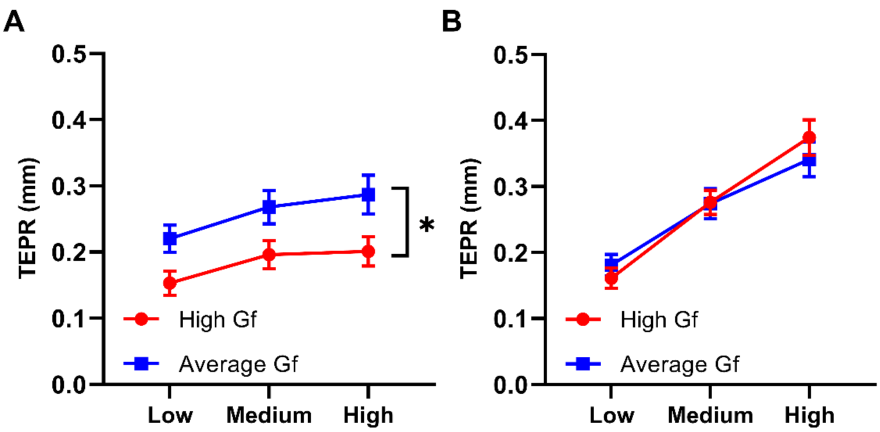


Figure 6 Task-evoked pupillary responses (TEPRs) of individuals with high and average fluid intelligence (Gf) in (A) exploitation and (B) exploration tasks with different difficulty levels. * p < 0.05

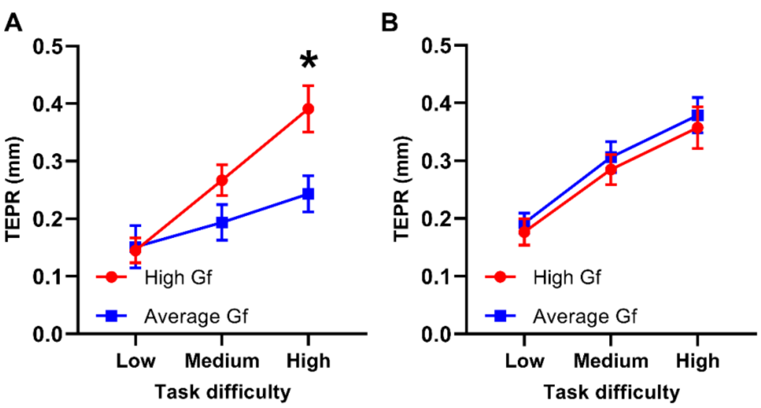


Figure 7 (A) Male and (B) female participants' task-evoked pupillary responses (TEPRs) in exploration tasks with different difficulty levels. * p < 0.05

4. Discussion

The results preliminarily supported our integrated control hypothesis, which posits that both task type and task difficulty influence the relationship between Gf and attentional resource allocation.

Behavioural results showed that high Gf participants performed better than average Gf participants in both accuracy and RT, which is reasonable and in line with numerous previous studies. With regard to TEPR results, both high and average Gf groups of participants showed larger TEPR as the task difficulty increased in both tasks, indicating that they allocated more attentional resources in highly demanding trials. Importantly, however, we found high Gf participants appeared to have more flexible resource allocation policies in different tasks. In the exploitation task, high Gf participants used significantly fewer attentional resources than those with average Gf in all difficulty levels, suggesting that task difficulty did not play a moderating role in exploitation tasks, which is consistent with the classic efficiency hypothesis (Ahern & Beatty, 1979; Haier et al., 1988) positing that brighter people can solve problems more efficiently; this result is also consistent with the integrated control hypothesis. In contrast, in the exploration task, high Gf participants tended to allocate more attentional resources than the average Gf individuals in the high-difficulty trials but not the low-difficulty trials, which is consistent with the former resource hypothesis and corresponding pupillometry and EEG studies (Bornemann et al., 2010; Doppelmayr et al., 2005; van der Meer et al., 2010) and the assumptions of the integrated control hypothesis. However, further analyses involving gender revealed that this phenomenon seemed only to exist in the male participants; thus, we further discuss the effect of gender in the following section.

The results above indicated that high Gf participants may have more flexible resource allocation patterns according to different task conditions. From the integrated control hypothesis perspective, high Gf individuals have better attention control ability and can dynamically regulate their task-relevant control state according to particular task demands. We argue that the neural efficiency of high Gf individuals may not only refer to their decreased resource consumption while solving tasks. Neural efficiency may also emphasize their ability to choose the optimal, goal-directed resource allocation policy and adapt brain activation to particular task demands (Dunst et al., 2014), which could maximize efficient processing across different tasks. Researchers studying intelligence theory have also claimed that intelligence largely depends on the capacity to regulate mental activity according to specific goals and intentions (Rueda, 2018), enabling flexible and rapid adaptation to changing conditions. This pattern economizes the use of attentional resources and renders the brain more efficient. In exploitation tasks, because the rules of solving problems were familiar to the participants, the high Gf individuals adjusted their control state to resource-saving exploitation close to automatization. In contrast, in the exploration task, which required constant exploration of the problem space instead of directly using existing rules, high Gf individuals might convert to higher-gain exploration as the task difficulty increased. In the low-difficulty trials, which were easy and showed fewer features of exploration according to the results of the interview, both high and average Gf participants could easily solve the problems with fewer resources. As the task demands increased, the high Gf participants might flexibly control their cognitive state and allocate more resources, while the average Gf individuals could only sustain their original resource allocation policy to solve problems with a relatively long reaction time and higher error rate. It should be noted that the behavioural results showed that high Gf males showed significantly higher accuracy than average Gf males in high-difficulty exploration trials, which might result from their more allocation of attentional resources. Therefore, the integrated control hypothesis could provide an appropriate account of the relationship between Gf and attentional resource allocation and reconcile the contradictions of previous studies.

In addition to the abovementioned findings, we found gender effects on the subjects' attentional resource allocation in both tasks, namely, the female participants invested significantly more resources than their male counterparts. Notably, there were nearly no behavioural differences between the men and women, indicating that the gender difference existed only in the resource allocation policy rather than in task performance. This result is consistent with a previous study's finding that males showed significantly less pupil dilation in a cube mental rotation task than females (Campbell, Toth, & Brady, 2018), suggesting that females tend to allocate more attentional resources to solve problems. Notably, the tasks used in Campbell et al.'s study (2018) and the present study were all visuospatial. As many studies show that male participants have an advantage in visuospatial tasks (Boone & Hegarty, 2017; Halpern, 2000), a reasonable explanation for the main effect of gender is that males require fewer attentional resources while solving these tasks due to their inherent visuospatial advantage. In the view of these explanations, as females usually show better performances in verbal tasks (Halpern, 2000), we predict that women would allocate fewer resources than men in verbal tasks. Previous studies using event-related desynchronization of alpha-band EEG as an index of resource allocation found that women were more efficient in solving verbal tasks, while men were more efficient in solving visuospatial tasks (Neubauer, Grabner, Fink, & Neuper, 2005), supporting the present explanation. In addition to task specificity, we can interpret the gender difference by the theory of *intelligence current* (Shi, 2004). This theory claims that social factors and one's personality could influence one's attitude regarding how to complete a specific task, which may further influence one's resource allocation in that task. Compared with males, females seem particularly cautious when performing cognitive tasks, such as mental rotation (Kerkman, Wise, & Harwood, 2001); this attitude towards tasks likely accounts for the increased resource allocation among the women in the present study.

Moreover, we found that gender played an important role in the exploration tasks between Gf and resource allocation. Our hypothesis that high Gf individuals allocate more resources during more demanding exploration tasks (resource hypothesis) was shown only in the males. To date, few pupillometry studies have explored the moderating role of gender. The pioneer pupillometry studies focusing on Gf and resource allocation that supported the resource hypothesis usually had a small sample size with a relatively small percentage of women, such as 8/37 (females/participants) (van der Meer et al., 2010), 13/66 (Dix & van der Meer, 2015), or 5/34 (Bornemann et al., 2010). The large proportion of male participants in these studies may have masked the interaction effect of gender, suggesting that the resource hypothesis in exploration tasks may not apply to females. In addition, according to the theory of intelligence current (Shi, 2004), individual differences in personality and attitudes towards tasks between males and females might be another reason for this finding. We noticed that both the high and average Gf females allocated resources equivalent to the high Gf males. The tendency of females to use more resources in visuospatial tasks may explain why there were no differences between the high and average Gf females in the exploration task.

Some limitations should be noted in this study. First, the integrated control hypothesis hypothesized that high Gf people allocate more resources in difficult trials of exploration tasks, which was not supported in female participants here. Considering the gender differences in cognitive domains, future studies might introduce verbal exploration and exploitation tasks favourable to females to explore whether the task domain or inherent gender differences lead to the moderating effect of gender between Gf group and resource allocation in the exploration tasks. Second, the two tasks used in this study are two examples of typical exploration and exploitation tasks, but they are not univocal (as shown in the results of the interview) and have some differences in physical properties. Future studies may find a single task with two separated conditions (one for exploration and the other for exploitation) to further verify this hypothesis. Last but not least, although the sample size in this study is adequate according to the calculation by G*Power, the relative unbalanced gender ratio in the average Gf group may lead to inadequate power for our analyses regarding gender. Future studies may consider more about larger sample size and better-balanced gender ratio.

In conclusion, to further elucidate the relationship between Gf and attentional resource allocation, the present study proposed a new hypothesis (i.e., the integrated control hypothesis) emphasizing both roles of task type and task difficulty in it. We found that high Gf participants allocated fewer resources at all difficulty levels than average Gf participants in the exploitation task. But in the exploration task, high Gf male participants allocated more resources in the high-difficulty levels than average Gf male participants. These results suggested that high Gf individuals tend to have better abilities to flexibly and adaptively allocated their limited attentional resources according to changing demands, which may be important characteristics of human intelligence.

Compliance with Ethical Standards

Funding This work was funded by the Pioneer Initiative of the Chinese Academy of Sciences, Feature Institutes Program, TSS-2015-06.

Conflict of interest The authors have no conflict of interest to declare.

Ethics statement The study has been performed in accordance with the ethical standards laid down in the 1964 Declaration of Helsinki and later amendments. Ethical approval had been obtained from the ethics committee of the Institute of Psychology, Chinese Academy of Sciences.

Informed consent Informed consent was obtained from all individual participants included in the study.

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Supplementary

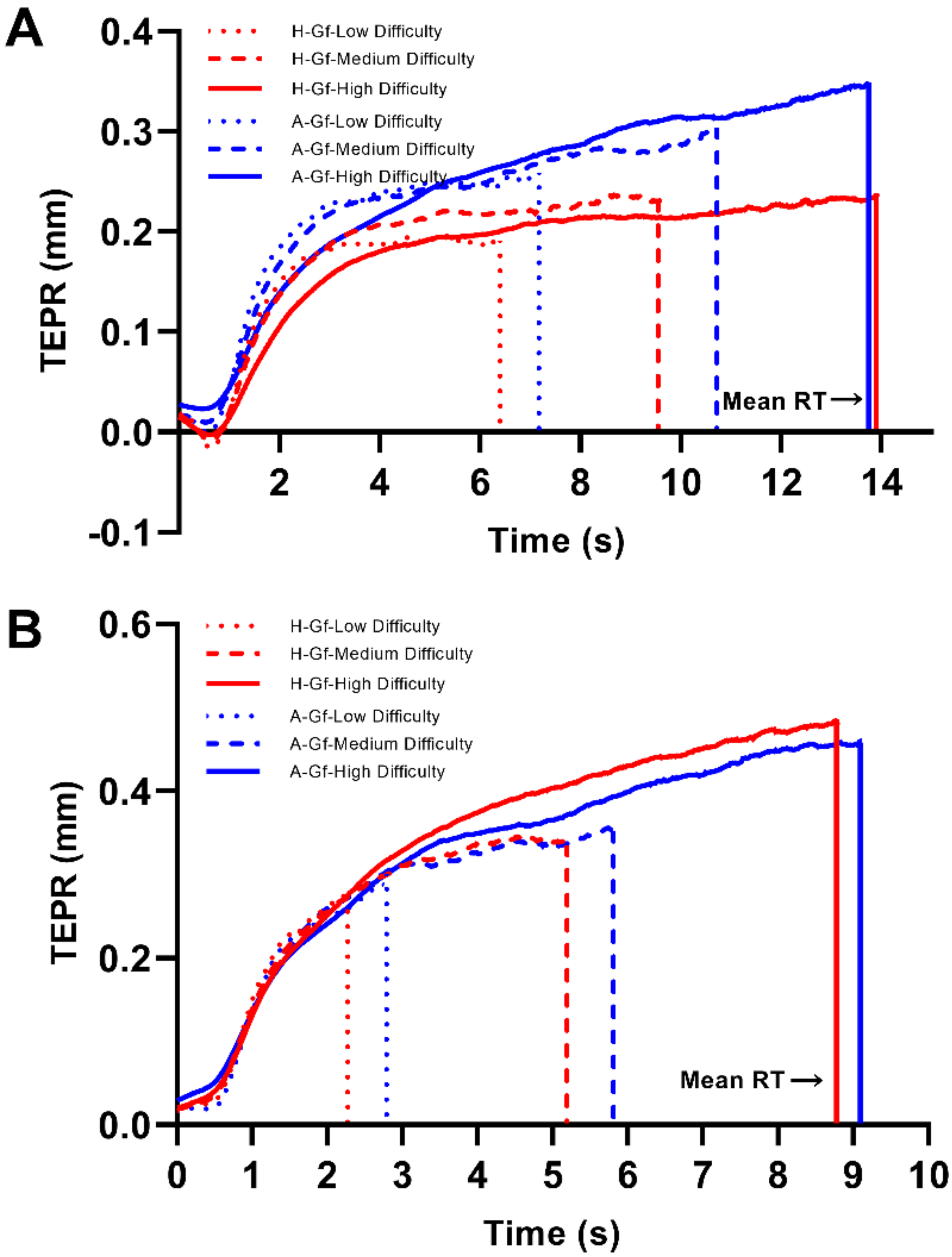

Figure S1 Pupillary time-domain waveforms and mean reaction times (RTs, vertical lines) of the high and average fluid intelligence (Gf) participants in (A) exploitation and (B) exploration tasks with different difficulty levels. H-Gf: high Gf individuals; A-Gf: average Gf individuals

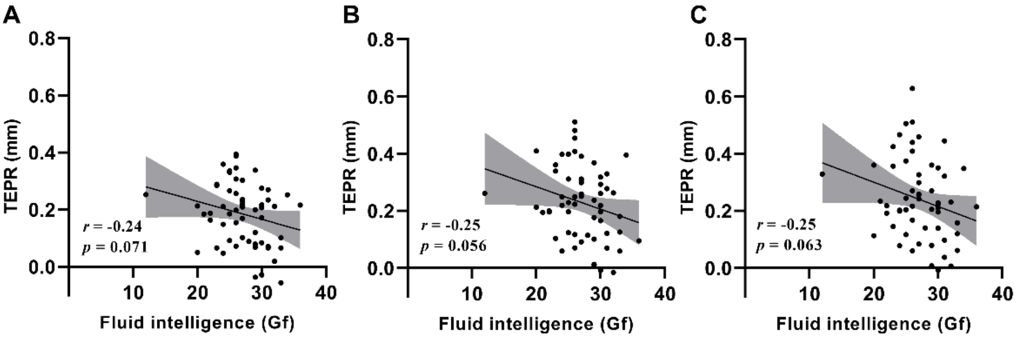

Figure S2 Correlations between fluid intelligence (Gf) and task-evoked pupillary responses (TEPRs) in the (A) low-difficult, (B) medium-difficult, and (C) high difficult exploitation task

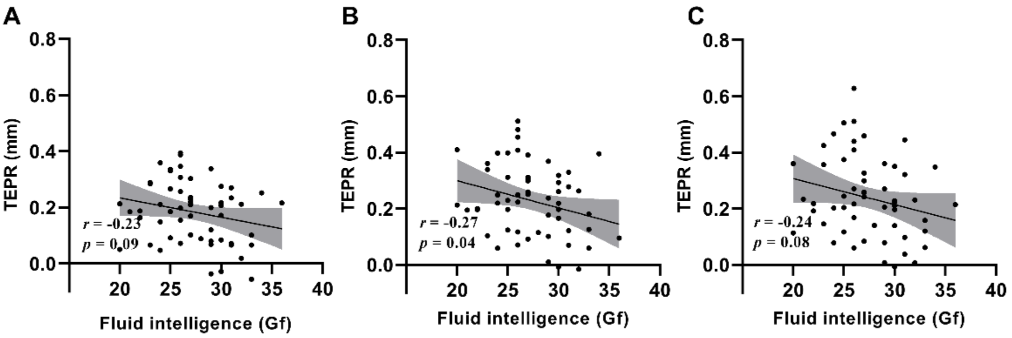

Figure S3 Correlations between fluid intelligence (Gf) and task-evoked pupillary responses (TEPRs) in the (A) low-difficult, (B) medium-difficult, and (C) high difficult exploitation task (without the outlier whose Gf = 12)

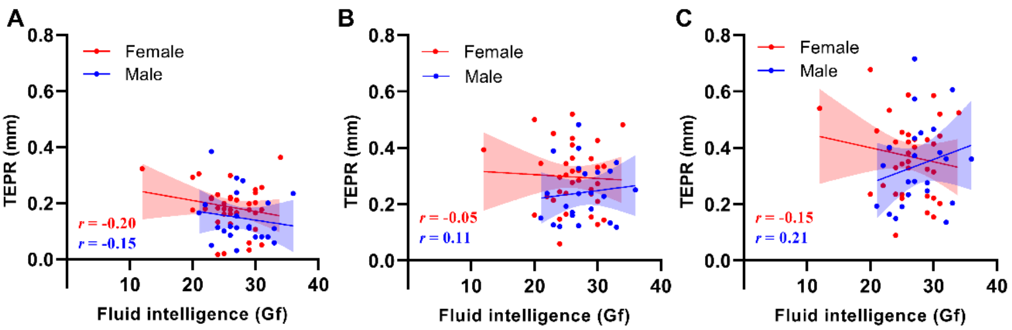

Figure S4 Correlations between fluid intelligence (Gf) and task-evoked pupillary responses (TEPRs) in the (A) low-difficult, (B) medium-difficult, and (C) high difficult exploration task

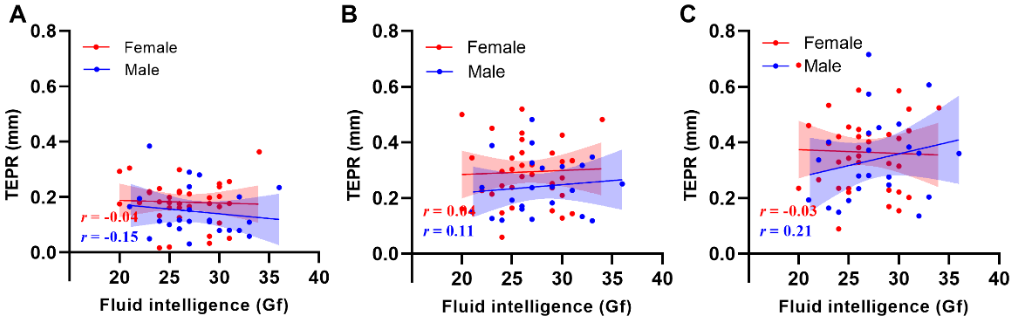

Figure S5 Correlations between fluid intelligence (Gf) and task-evoked pupillary responses (TEPRs) in the (A) low-difficult, (B) medium-difficult, and (C) high difficult exploration task (without the outlier whose Gf = 12)