NEURAL ADAPTABILITY AND INSPECTION TIME

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Abstract

A measure known as inspection time (IT) has been shown to account for approximately 25% of the variance in peoples' intellectual abilities, as measured by IQ. Despite this strong relationship, inspection time has had only limited success in expanding our knowledge regarding the nature of intelligence, which can be attributed to a lack of understanding of the neurophysiology underlying IT. In the present study we present a hypothesis in which a participant's IT is determined by their brain's ability to adapt its neural functioning based on experience. This ability is often referred to as neural plasticity. To test this hypothesis, we related participants' ITs to a series of neural plasticity measures identified during a spatial learning task and a reinforcement learning task. In both tasks a significant correlation was found; however, the correlations found were in opposing directions. A subsequent analysis of the tasks revealed a potentially significant relationship between participants' learning ability and their focus of attention. This led us to the conclusion that IT may be determined by participants' neural plasticity through a measure known as neural adaptability, which relates participant experience, learning, and attention.

Keywords: Inspection Time, Intelligence, Neural Plasticity, Neural Adaptability, Spatial Learning, Reinforcement Learning

1. INTRODUCTION

Individual differences in intelligence can be measured using standardized tests; for example, the Wechsler Adult Intelligence Scale (WAIS) [1], the Woodcock-Johnson Psycho-Educational Battery-Revised (WJ-R) [2], or Raven's Progressive Matrices [3]. A very active avenue of research has aimed itself at discovering the neurophysiological source of these differences. One method that has been somewhat successful in relatively recent history is to relate individual differences in measured intelligence (IQ) to measures of basic neural processes [4]. For instance, based on the results of several studies that relate reaction time to IQ, Jensen hypothesized that: "Loss of information due to overload interference and decay of traces that were inadequately encoded or rehearsed for storage or retrieval from LTM [long-term memory] results in 'break-down' and failure to grasp all the essential relationships among the elements of a complex problem needed for its solution" [5, pp. 122]. Jensen further hypothesized that this 'break-down' of information encoding may potentially be avoided by faster brains (i.e., those that exhibit faster processing speeds). Nevertheless, reaction time paradigms have atrophied due to modest correlations with IQ and a lack of theoretical tractability in accounting for the individual differences in intelligence [6,7].

Another measure, inspection time (IT), has since been shown to account for a relatively large portion of the variance in individual differences in intelligence as well as provide a stronger theoretical rationale for its relation to IQ [7]; the estimated, corrected correlation between IT and IQ is -0.50, or, another way, IT accounts for approximately 25% of the variance in IQ scores [7-9]. Indeed, the link between IT and mental abilities is one that has been replicated many times [e.g., 10-13]. One consistent finding by Burns et al. [11-13] is that IT correlates with a factor of intelligence from the Gf-Gc theory [14] known as general speed of processing (Gs; a factor of intelligence that refers to the ability or speed at which one is able to perform easy or over-learned problems).

IT is most often measured by a simple two-choice forced-discrimination task. The task begins by focusing participants' attention using a simple visual cue (see Figure 1a). Following the cue and a short, random delay, the target stimulus (see Figure 1b) –referred to as the pi-figure due to its resemblance to the Greek letter Π– is

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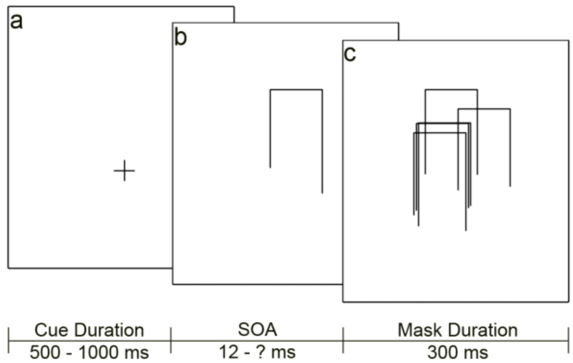

Fig. 1 Figures used in the IT task: (a) the cue figure, (b) the stimulus (pi-) figure, and (c) the backward-mask figure.

presented for some predetermined period of time. Two potential target figures exist, one in which the right leg of the pi-figure is slightly longer and one in which the left leg is slightly longer. Immediately following the presentation of the target stimulus, a mask (see Figure 1c) is presented to disrupt any visual persistence that may be available in the form of iconic storage. Since the mask essentially works backward in time (i.e., it disrupts the perception of previously presented visual stimuli), the mask is considered a 'backward-mask'. Participants' task is to determine which leg of the target stimulus was longer (or shorter). The pertinent measure of the IT task is the period of time between the onset of the target stimulus and the onset of the mask (SOA: stimulus onset asynchrony). The IT task was designed such that, given a long enough SOA, the task can be completed perfectly by participants with a wide range of intellectual abilities; however, by reducing the SOA to the order of tens of milliseconds, chance performance levels can be reached. The task is repeated using a range of SOAs until a critical SOA (CSOA) can be confidently identified under which the participant performs the discrimination at a preset accuracy level (e.g., 75%); IT is operationally defined as this CSOA. Despite the success that IT has achieved in relating IQ to a simple cognitive task measure, issues still exist that have –so far– prevented IT from revealing the neurophysiological basis underlying the relationship between IT and IQ.

Garlick [15] has presented a hypothesis about how the structure of the brain may lead to the phenomena embodied by individual differences in intelligence. In his hypothesis, Garlick argues that the power of the brain is inherently stored in the connections between neurons: "Rather, the neuron is a relatively simple processing unit that operates independently of other neurons and whose firing is determined by changing the connection between itself and the other neurons (Judd, 1990) [16]. Therefore, this argues for a critical role for the connection in the production of meaningful output." [15, pp. 118].

The basic tenet of Garlick's hypothesis is that, within the general population, individual differences exist in the brain's capacity to organize itself based on experience, which is often referred to as neural plasticity. As a result of these differences in neural plasticity: "individuals with more plastic brains would be more highly developed at all intellectual abilities, irrespective of their superficial characteristics." [15, pp. 121].

Burns et al. [17] have recently tested an intriguing hypothesis regarding individual differences in intelligence based on the theorizing of Garlick about the role of neural plasticity in intelligence. In their study, they attempted to determine if measures of perceptual learning during the IT task and a motion discrimination task are related to intelligence factors obtained from a subset of tests in the Woodcock-Johnson Battery-Revised [2]. A single correlation of $r = 0.35$ between perceptual learning in the IT task and Gs was found, and the conclusion that: "Such a parameter may at least partially define a general intelligence factor." [17, pp. 97] was reached.

Although it was not discussed by Burns et al., neural plasticity could be more generally related to IT; that is, a participant's IT could be considered to be indicative of the efficiency of one's basic visual processing areas as a result of their individual neural plasticity. Under this assumption, participants with more plastic brains will have more efficient visual processing areas, which would result in quicker processing of visual stimuli –and a lower IT. One prediction made by such an interpretation of IT is that participants who are adept at the IT task should also be adept at other simple visual tasks; indeed, this was found by Garaas & Pomplun [18], which begs the question, how might having more efficient visual processing areas result in lower ITs? To answer this question, it is necessary to further examine the nature of the task used to measure IT.

Since the inception of IT, a number of theories have been put forward to resolve the cognitive processes of which IT is a measure. Originally, IT was regarded an estimate of the time required to make a single, discrete sensory observation [19]. Subsequently, following the broader research of visual masking studies, White [20,21] refuted the original theory in lieu of a theory that places IT as a measure of participants' temporal resolution. Essentially, using the integration theory of visual masking, White's theory states that during sufficiently short SOAs, the stimulus and mask figures become integrated into a single figure, thus preventing successful discrimination of the longer leg in the pi-figure.

However, the visual masking theory on which White's theory of IT is based has since been shown to be incorrect due to its inability to account for a handful of observed effects found in various visual masking studies

[22]. For instance, certain masks that do not overlap spatially with the target –a prime example is a mask with four dots placed at the corners of an invisible box surrounding the stimulus– can produce masking effects [22], which cannot be explained by the integration theory.

As an alternative, Di Lollo et al. [22] provide an account of visual masking which factors in recent neuroanatomical and psychophysical evidence. Their theory, the object substitution theory of visual masking [23], involves a recurring neural loop between higher- and lower-order visual areas that is used to process visual stimuli for conscious perception. This theory gives feedback connections that transmit visual information from higher-order visual areas (e.g., V5) to lower-order visual areas (e.g., V1) a critical role in the perception of visual stimuli, which has been verified by transcranial magnetic stimulation (TMS) studies [24,25]. In an interpretation of these TMS studies in which conscious perception of a visual stimulus is interrupted by TMS applied to area V1 following activation by the stimulus of area V5 and higher, Bullier [26] proposed that an early wave of activation is conveyed by the magnocellular pathway (transient motion-related signals) through the hierarchy of visual areas; the computations of the higher-order visual areas are then projected back to the lower-order visual areas to aid in the processing of visual information transmitted by the slower parvocellular pathway (sustained form-related signals), and, if this process is interrupted, conscious perception of the visual stimulus is blocked. Based upon a view of visual processing involving critical feedback projections, the backward mask presented during the IT task can be considered to disrupt successful discrimination at sufficiently short SOAs by interfering with the secondary processing by lower-order visual areas receiving feedback projections. Specifically, following the presentation of the mask, when the projections from higher-order visual areas reach lower-order visual areas, the target stimulus is no longer driving the feedforward processing and the two converging signals no longer match each other; thus, conscious perception of the target stimulus is effectively blocked. From this interpretation, IT represents a speed processing that is based upon the efficiency of the neurons (or neural connections) that comprise the feedback loop.

To test this theory of IT, we had participants perform the standard IT task as well as two tasks that test participants' learning abilities from which we derived various measures of neural plasticity. We hypothesize that a positive correlation should exist between IT and the measures of neural plasticity since, in this theory, IT represents a level of neural efficiency that is a direct result of participants' individual neural plasticity. The first learning task is the contextual cueing task, in which participants can be shown to significantly improve their reaction time by implicitly learning the visual context of a target item. The second task, the Iowa Gambling Task, provides a measure of participants' ability to learn the risks and rewards associated with previous experiences. These tasks represent the broader categories of spatial learning and reinforcement learning, respectively.

2. INSPECTION TIME TASK

2.1 Method

2.1.1 Participants. The IT task was carried out with the participation of 36 naïve individuals. Participants were paid a $20 honorarium for their participation. The average age of the participants was 28.4 ± 11.7 (s.d.) years and the average number of years of education of participants was 14.8 ± 1.8 years. All of the participants had intact vision and some used corrective lenses. In accordance with the Helsinki Declaration of Human Rights, participants were given full disclosure about their role in the task, and written informed consent was obtained from all participants. The study was conducted with the approval of the Institutional Review Board at the University of Massachusetts Boston.

2.1.2 Apparatus. Stimuli were presented on a 21-inch Dell P1130 monitor using the resolution 1024×768 and a refresh rate of 85 Hz. Participants sat approximately 40 cm from the screen, resulting in a horizontal and a vertical viewing angle of 56.9° and 42.7°, respectively. Participants' responses were obtained using a standard PC mouse.

2.1.3 Materials. Participants' ITs were recorded using a slight variation of the standard IT task, which is very similar to that used by Garaas & Pomplun [19]. In total, four figures were used during the IT task: a cue figure, two target figures, and a mask figure. The cue figure consisted of a simple cross subtending 2.2° in both width and height (see Figure 1a). The two target figures (i.e., pi-figures; see Figure 1b) consisted of two parallel vertical lines connected at their tops by a horizontal line. The longer vertical line was 11.1° in length; the shorter vertical line was 8.3° in length; and the horizontal line was 5.6° in length. The mask figure consisted of five pi-figures randomly presented up to 2.6° from the center of the target stimulus (see Figure 1c). Both vertical lines (i.e., legs) of the pi-figures in the mask were of the longer variety.

2.1.4 Procedure. Participants completed 300 trials of the IT task, where each trial consisted of the presentation of a cue, target stimulus, and mask. The cue was presented for a random period of time that varied between 500 and 1000 ms in the lower-middle of the screen. Immediately following the presentation of the cue, one of the two potential target stimuli was presented for a preset amount of time (SOA). It was random as to which version of the target stimulus was presented during any given trial. Immediately following the target stimulus, the mask was presented for 300 ms.

To familiarize participants with the task, six initial trials were presented using SOAs 800, 800, 800, 560, 320, and 160 ms respectively. Following the presentation of the mask, participants pressed either the left or right mouse button to indicate they believed that the longer leg of the target stimulus was on the left or right side, respectively. Participants were instructed to take as long as they needed to respond to a trial. Following the initial trials, participants completed the 300 trials in pairs, with the first pair of trials using an SOA of 80 ms. Pairs of trials continued thereafter such that if a participant responded correctly to both trials of a given pair, the next pair had their SOAs decreased by 11.8 ms; whereas, if either trial was responded to incorrectly, the SOAs were increased by 11.8 ms. Participants' ITs were determined by fitting a sigmoid curve to the accuracy of their responses as a function of the SOA and taking the SOA at which the curve crossed 75% accuracy. Figure 2 illustrates an example curve-fitting for a single participant's responses during the IT task.

2.2 Results & Discussion

Results were obtained for all but six participants whose responses were too erratic to allow for a confident determination of their IT. The mean IT of the remaining 30 participants was 72 ± 37 (s.d.) ms. ITs recorded here are similar to those recorded using a similarly designed IT task [18].

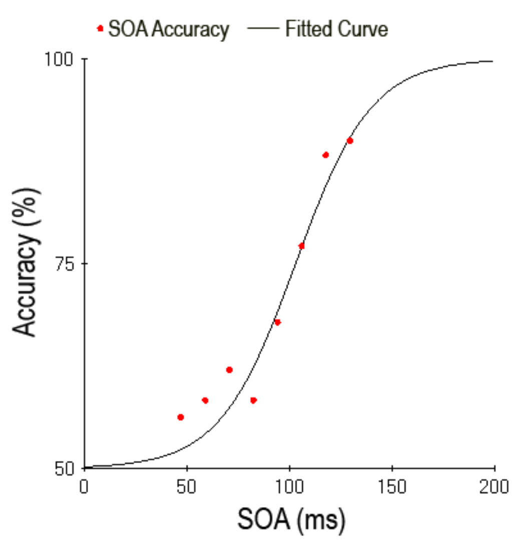

Fig. 2 A sample psychometric curve for a single participant from the IT task.

3. CONTEXTUAL CUEING TASK

Contextual cueing represents a robust collection of visual search tasks in which participants are able to improve reaction times by implicitly learning the spatial configuration of distractor items (i.e., the visual context); see Chun [27] for a review. In the traditional form of contextual cueing tasks –from which the task presented hereafter was modeled–, participants search for a target item (T) among a series distractors (L; see Figure 3). The task is divided into a series of blocks such that half of the trials within a given block are presented every block. In this way, participants' reaction times progressively decrease as they implicitly learn the spatial configuration of distractors. Contextual cueing effects are often referred to in the broader context of biasing perceptual processing mechanisms in favor of perceiving more likely situations. For instance, objects (e.g., a traffic light) may be located and perceived more quickly in situations that resemble their natural state (e.g., a street corner) [28].

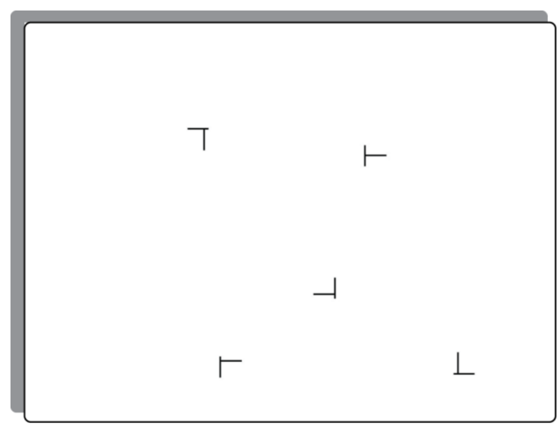

Fig. 3 Sample display from the contextual cueing task.

The learning that takes place during the contextual cueing task is implicit (subjects cannot verbally report whether they had previously seen a given display or not above chance levels [29]), long term (learning effects persist for at least a week [30]), and robust, which makes it an ideal task to study the neural plasticity of participants. Following our primary hypothesis, we expect participants who exhibit a lower IT to demonstrate greater reaction time improvements as a result of learning the visual context of the target items.

3.1 Method

3.1.1 Participants and Apparatus. All 36 participants that completed the IT task also completed the contextual cueing task. The apparatus used during the IT task was also used for the contextual cueing task.

3.1.2 Materials. In total, 252 displays were generated prior to testing participants. These displays included 12 repeated ("old") displays to be presented in every block of trials and 20 sets of 12 new displays which were to be presented exactly once during the experiment. Each display contained a single target item and four distractor items presented on a white background. Distractor and target items subtended a visual angle of 2.2° in both width and height and were separated by at least 8.3°. Distractor items contained a small offset of 0.3° at the junction of the horizontal and vertical lines to produce a more difficult search. Targets and distractors could assume one of four potential orientations, which were balanced across each block of trials.

3.1.3 Procedure. Participants completed twenty blocks of trials during the contextual cueing task. Each block was composed of twenty-four trials; twelve trials contained an old display, and twelve trials contained a new display. The order of old and new trials was randomized before the start of each block. Participants were instructed to find the target in each trial as quickly and accurately as possible and to report its orientation by pressing one of four arrow keys on a standard keyboard. If participants did not respond within ten seconds, the trial resulted in a timeout and was counted as an incorrect response. Following a response or timeout, a sound was played to indicate the result of the trial.

3.2 Results & Discussion

Accuracy during the contextual cueing task was very high at 98% ± 2%. Trials that were responded to incorrectly or ended in a timeout were not included in the analysis of reaction time measures. In an effort to remove noise, every two blocks of trials were grouped together to form an epoch, as has been done previously [31]. Figure 4 illustrates the average reaction times in old and new trials for each epoch. The average reaction time for all trials during the first epoch was 1921 ± 706 ms, and the average reaction time during the last epoch was 1598 ± 354 ms. Contextual cueing effects are calculated as the difference between old and new trials in the final epoch. During the final epoch of the task, the average reaction time for old trials was 1512 ± 334 ms, and the average reaction time for new trials was 1676 ± 393 ms. Thus, the average improvement in reaction time due to contextual cueing was 163 ± 155 ms, which is on par with previous reports [e.g., 29,31The average response times in old and new trials during the final epoch were significantly different, $t(35) = 6.30$, $p < 0.001$. In an attempt to extract a maximum effect of contextual cueing, the greatest difference between old and new trials for a single epoch was calculated, which we will refer to as epoch-best. The average value for epoch-best was 371 ± 160 ms.

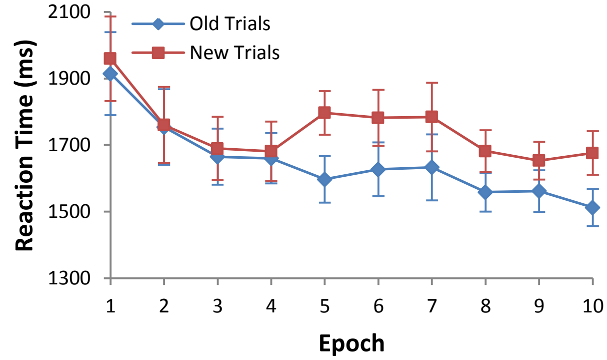

Fig. 4 Average reaction times of old and new trials in each epoch of the contextual cueing task.

4. IOWA GAMBLING TASK

Any serious discussion regarding higher-cognitive functioning must include some aspect of decision making. What are the factors that influence our decision making process? What are the basic processes that allow us to choose one option over another? Given the importance of decision making in basic survival, it is not surprising that much effort has been put forward by the scientific community towards answering questions such as these. To this end, a plethora of experimental tasks have been created to study the individual aspects of decision making; one such task is the Iowa Gambling Task (IGT). IGT was created by Bechara et al. [32] to study emotional effects in decision making; however, other researchers have noted that IGT can also be used to study decision making in general [e.g., 33]. In IGT, participants repeatedly select cards from four decks; two decks will result in long-term gains, while the other two will result in long term losses, even though single pulls may not always reflect this pattern.

IGT was largely chosen for this study because of the depth of knowledge regarding reinforcement learning and the governing neural structures; see Dayan & Balleine [34] for a review. As with the previous task, we expect lower-IT participants to learn the risks and rewards associated with each deck more quickly and, as a consequence, to select cards from advantageous decks more often; ultimately resulting in more money earned during the task. Assuming the hypothesis holds true, it may seem reasonable to explain low-IT participants' performances as a result of their greater intellectual ability. However, previous studies involving IGT suggest that participants begin learning the risks and rewards of each deck prior to any conscious realization [35]. Bechara et al. [35] measured skin conductance as participants completed the task and found that normal participants generated anticipatory skin conductance when contemplating a risky decision prior to conscious realization of the risk involved. Therefore, it seems reasonable to consider IGT a measure of neural plasticity rather than a measure of participants' ability to develop overt strategies [35].

4.1 Method

4.1.1 Participants and Apparatus. All 36 participants that completed the IT task also completed the contextual cueing task. The apparatus used during the IT task and contextual cueing task also served as the apparatus for IGT with one small exception, the software used to test participants on IGT was created by Psychological Assessment Resources, Inc.

4.1.2 Materials. Four illustrated decks of cards, lined up horizontally, were presented on a green background, above which, participants' current money earned or debt incurred was presented; the decks were labeled A, B, C and D. Decks A and B are considered losing decks, as their repeated choice will lead to long-term losses; decks C and D, on the other hand, are considered winning decks, as their repeated choice will lead to long-term gains.

A single click of a standard mouse was used by participants to indicate from which deck they wished to choose. Following a participant's choice of a deck, a red card was presented for X ms over the chosen deck. While the red card was being presented, the monetary result of the choice was presented below the card in black (gain) or red text (loss).

4.1.3 Procedure. Participants were asked to pick 100 cards from the four decks in any manner they deemed most appropriate to acquire the largest gains. Participants were given a $2000 loan in play money that would need to be paid back at the end of the task. Regardless of how participants performed, no real money was exchanged during the task. Prior to participants' selection, the message, "Pick a Card" was displayed to participants, and following their selection, the red card and monetary result were presented, which was then followed by the start of the next trial.

4.2 Results & Discussion

Participants had some trouble avoiding the large losses hidden in decks A and B, as the average amount of money acquired at the end of the task was -$722 ± $1289, which included repayment of the $2000 loan. To facilitate the analysis of participant learning, participants' selections were broken up into a series of five blocks with twenty selections per block. Figure 5 illustrates the proportion of participant selections per block that were from advantageous or disadvantageous decks. During the

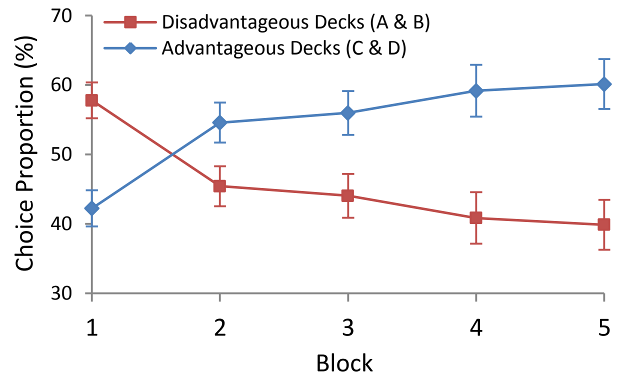

Fig. 5 Average percentage of card selections from advantageous and disadvantageous decks.

first block, participants were more likely to choose from disadvantageous decks, equaling 58 ± 16% of their selections, than advantageous decks; however, by the second block of trials, participants were more likely to choose from advantageous decks, equaling 55 ± 17% of their selections. Learning increased, albeit to a lesser degree, as the task continued; in the last block, participants selected from advantageous decks 60 ± 22% of the time. A one-way Analysis of Variance (ANOVA) revealed a significant main effect for block number $F(4) = 4.99$, $p < 0.005$, and the only significant difference in the proportion of deck selections between two sequential blocks of trials occurred amid the first and second block, $t(35) = 2.97$, $p < 0.005$; all other ps > 0.10. Two neural plasticity measures were identified for IGT, the proportion of selections from advantageous decks during the final block of the task, and the difference between the proportion of selections from advantageous decks during the first and last blocks, which was 19 ± 32%.

5. RELATIONSHIP ANALYSES

A bivariate, two-tailed correlation was performed to test the ability of IT to predict the various measures of neural plasticity that were identified in the contextual cueing task and Iowa Gambling Task. To determine if a ranked correlation was more appropriate, a Shapiro-Wilk test for normality was conducted, which revealed that IT does represent a normal distribution ($df = 30$, statistic = 0.94, $p > 0.05$); therefore, Pearson's correlation measure r will be used. See Table 1 for a summary of the relationships between IT and the measures of neural plasticity.

5.1 Contextual Cueing

Evidence for a significant relationship was found between IT and one of the two neural plasticity measures identified for the contextual cueing task. The first measure identified for the contextual cueing task was a measure of reaction time differences between old and new trials during the final epoch. This measure represents participants' spatial learning of old display configurations (cc-learning), which did not correlate with IT, $r = 0.10$, $p = 0.62$. To remove fatigue-related effects, the maximum difference between reaction times during old and new trials in a single epoch was computed (cc-best), which was found to correlate significantly with IT, $r = 0.54$, $p < 0.005$. Unexpectedly, the significant relationship between IT and cc-best is opposite of that predicted by the hypothesis placed forward in the present study, which will be discussed in detail below. Additionally, significant correlations between IT and the reaction times from both the first and last epoch were also found, $r = 0.59$, $p < 0.005$, and $r = 0.62$, $p < 0.001$, respectively. Therefore, even though high-IT participants were able to learn better during the contextual cueing task, low-IT participants still demonstrated significantly shorter reaction times. The finding that low-IT participants are faster at performing the contextual cueing task was expected, as significant correlations between IT and various reaction time measures during other visual search tasks have been found [18].

Table 1 Correlation (r) between IT and neural plasticity measures. * = $p < 0.01$, ** = $p < 0.001$

measure	r (p)
cc-learning	0.10 (0.62)
cc-best	0.54 (0.00)*
igt-last	-0.60 (0.00)**
igt-learning	-0.47 (0.01)*

5.2 Iowa Gambling Task

Two measures of neural plasticity were identified for IGT: the difference between the proportion of advantageous selections made during the first and last blocks of trials (igt-learning), and the proportion of selections made from advantageous decks during the final block of trials (igt-last). A significant correlation was found between IT and igt-learning, $r = -0.47$, $p < 0.01$, and igt-last, $r = -0.60$, $p < 0.001$. Unlike the contextual cueing neural plasticity measures, the neural plasticity measures from IGT do demonstrate the hypothesized relationship.

5.3 Discussion

The results of the relationship analyses between IT and the various neural plasticity measures paint a somewhat less-than-clear portrait. Both learning tasks demonstrated a significant correlation between IT and the measures of neural plasticity. However, individual analyses of these two tasks revealed significant relationships in opposing directions. In the analysis of the contextual cueing results, it was found that participants who were less adept at performing the IT task (i.e., those with slower processing speeds) showed significantly larger improvements as a result of contextual cueing effects. On the other hand, the results of the IGT analysis demonstrated the opposite relationship between IT and the task's neural plasticity measures. These results suggest that the hypothesis put forward by this study is incorrect, at least at a general level. Alternatively, it could be that the hypothesis does not take into account all factors related to the learning tasks presented. This possibility is discussed below.

Previous studies involving contextual cueing have noted a very interesting effect similar to the one found in the present study. It has been shown that participants with dyslexia actually demonstrate higher learning of the spatial relationships in repeated (old) displays [36]. This remarkable result has been explained in the context of dyslexic participants employing a more distributed attentional landscape [37]. Is it possible that the effect observed in the present study is analogous to the one involving dyslexic participants? Interestingly, previous hypotheses regarding IT have considered that IT may provide an index of a person's ability to orient attention [38]. Furthermore, Scheres et al. [39] found reduced striatal activation –striatal activations have been demonstrated to correlate with performance in reinforcement learning tasks similar to IGT [40]– in adolescents with ADHD during reward anticipation. Therefore, it appears that participants' ability to effectively direct their attention to relevant stimuli is a crucial aspect of the reinforcement learning that takes place in tasks such as IGT. Taken together, these data concerning the tasks involved suggest that the focus of attention may have a critical role in establishing the neural mechanisms underlying the learning that takes place.

6. Conclusion

In the present study, we presented a hypothesis regarding IT which ascribes the neurophsyiological source of differences in IT to differences in the computational efficiency of participants' basic visual processing areas as a result of having more 'plastic' brains. We then tested this hypothesis by relating participants' ITs to various measures of neural plasticity identified during a spatial learning task and a reinforcement learning task. Both tasks demonstrated a significant relationship between IT and the participants' neural plasticity; however, these relationships were found to be in opposing directions. A subsequent comparison of previous studies involving spatial learning and reinforcement learning revealed distinct deficits in participants with opposing disorders. Participants with problems focusing attention (i.e., participants with dyslexia) have been shown to learn better during contextual cueing tasks whereas participants with similar problems focusing attention (i.e., participants with ADHD) have been shown to learn worse during reinforcement learning tasks.

For these reasons, we modify our initial hypothesis by including a significant role of attention; that is, we propose that participants with a low IT do possess greater neural plasticity, except this neural plasticity relies critically on the attentional modulation of the actual neural pathways where the learning takes place. Interestingly, this new hypothesis is very similar to a hypothesis that was tested briefly in the later part of the 20th century. This hypothesis involved a measure known as neural adaptability [41] that was expressed as smaller evoked potentials to stimuli that were learned through previous experience to be non-relevant, and larger evoked potentials to novel stimuli. This measure was subsequently shown to correlate significantly with measures of intelligence. Future studies will be directed towards investigating the role of attention in relating IT to participants' ability to learn during various tasks. Additional studies will also be performed to determine if a relationship exists between the theories regarding neural adaptability and IT.

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