



Psychophysiological indices of cognitive style: A triangulated study incorporating neuroimaging, eye-tracking, psychometric and behavioral measures[☆]



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ABSTRACT

Employing a triangulated design to explore psychophysiological indices of cognitive style, the study investigated the validity of the intuition-analysis dimension of cognitive style and its associated construct measure, the Cognitive Style Index (CSI). Participants completed a comparative visual search (CVS) task whilst changes in hemodynamic concentrations in the prefrontal cortex (PFC) were monitored using functional near-infrared spectroscopy and eye movements were recorded together with task performance measures of response time and accuracy. Results revealed significant style-related differences in response time and number of saccades. Analysts were characterized by fewer saccadic eye movements and quicker response times—but with comparable accuracy scores—compared to intuitives, suggesting a more efficient visual search strategy and decision-making style on the experimental task. No style-related differences in neural activation were found, suggesting that differences were not mediated by style-specific variations in brain activation or hemispheric lateralization. Task-evoked neural activation—compared with baseline resting state—represented the value of PFC-based neural activation measures in studies of cognitive processing. Findings demonstrated style-related differences supporting the intuition-analysis dimension of cognitive style and the validity of the CSI as a psychometric measure of style. The potential value of valid psychometric measures of cognitive style in applied areas is highlighted.

1. Introduction

Cognitive—or information-processing—style refers to cognitive strategies consistent over both time and activity (Sternberg & Grigorenko, 2001) that govern the way an individual habitually acquires, processes, and interprets information. Thus, cognitive style reflects individual differences in information-processing that are the focus of familiar frameworks of human thinking such as Epstein's (1990) Cognitive-Experiential Self-Theory and Kanheman's (2011) fast and slow thinking. Distinct from cognitive ability (Sternberg, 1997), style is key to fundamental human processes such as decision-making, perception, and learning (Hough & Ogilvie, 2005; Riding & Sadler-Smith, 1997). As such, cognitive style is a construct central to a range of disciplines and fields including cognitive and social psychology, education, business, and management (Koshevnikov, Evans, & Kosslyn, 2014). Accounting for style has been found to promote learning potential and enhance work-related performance (Hayes & Allinson, 1996;

Riding & Agrell, 1997; Sadler-Smith, Allinson, & Hayes, 2000). Some studies, for example, suggest that delivering educational material in a format suited to the individual's preferred cognitive style significantly improves learning outcomes (Ford & Chen, 2001; Yang, Hwang, & Yang, 2013). Style has also been found to have a direct impact on the development of managerial strategies and entrepreneurial innovation (Allinson, Chell, & Hayes, 2000; Visser & Faems, 2015).

Whilst the utility of cognitive style seems evident, the field has suffered a period of heavy criticism, with the existence of over 71 different conceptual models of style (Coffield, Moseley, Hall, & Ecclestone, 2004) and a plethora of seemingly arbitrary construct definitions and associated measures, inciting confusion amongst researchers and practitioners alike (Cassidy, 2004). This has raised questions regarding both the validity of the conceptualization of style and, in particular, existing self-report psychometric construct measures of style and their widespread use in both research and applied contexts (Cassidy, 2012; Coffield et al., 2004). Capitalizing on the potential of style to afford

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optimal fit between the individual and a particular functional environment is conditional on the capacity to effectively measure the construct. In view of criticisms levelled at existing approaches to style measurement, the present study explores the potential in adopting a neuroscientific approach combined with eye-tracking and psychometrics for the study of cognitive style, and in doing so offer validation data supporting existing self-report psychometric measures of style which, in turn, will facilitate work exploring the construct in applied settings.

Based on the assumption that style is reflective of underlying cognitive functioning (see Koshevnikov et al., 2014 for a review), it is argued that there exists potential to validate the construct through the identification and exploration of psychophysiological indices (Bendall, Galpin, Marrow, & Cassidy, 2016). The ability to identify style-dependent traits in neurological mechanisms and perceptual strategies would offer a unique insight into the functional expression of style, confirm construct validity of the psychometric instrument under investigation, and, most crucially, serve to consolidate and substantiate the conceptual basis of cognitive style.

1.1. The intuition-analysis dimension of style

Despite a range of available conceptualizations of human information-processing, and perhaps due to its association with speed and accuracy in decision making and thus its inherent value, the distinction between intuitive and analytic processing is prevalent in cognitive style research and practice (Dane & Pratt, 2007; Hodgkinson & Sadler-Smith, 2003). For example, intuitive-analysis processing has been used to investigate diagnostic decision making in medical students (Tay, Ryan, & Ryan, 2016) and dominant thinking style in judges (Guthrie, Rachlinski, & Wistrich, 2007), highlighting the relevance of this particular conceptualization of information processing in critical areas of human functioning. This fundamental distinction is a central feature of influential theories of information processing including Epstein's integrative personality theory Cognitive-Experiential Self-Theory (Epstein, 1990; Epstein, Pacini, Denes-Raj, & Heier, 1996) and Kanheman's (2011) System 1 and System 2 thinking. Although using different conceptual labels, both Epstein's Rational and Experiential thinking and Kahneman's System 1 and System 2 thinking represent the familiar distinction between analytic and intuitive processes. Active when the situation is routine and time-constrained, Experiential and System 1 thinking are commonly described using the terms pre-conscious, automatic, concrete, holistic, affect-free, fast, effortless, experiential, automated, subconscious, based on pattern recognition and past experience, and, critically, intuitive. More cognitively demanding and active when the situation is complex or involves uncertainty, Rational and System 2 thinking are commonly described using the terms conscious, deliberate, abstract, logical, affect-laden, slow, effortful, based on past learning with the conscious application of rules, and, critically, analytic (Epstein et al., 1996; Hodgkinson, Sadler-Smith, Sinclair, & Ashkanasy, 2009; Kahneman, 2002; Kahneman & Frederick, 2002; Tay et al., 2016). The Cognitive Style Index (CSI; Allinson & Hayes, 1996) is a self-report psychometric measure of cognitive style that specifically assesses preference-related differences in information processing according to intuition and analysis. Whilst a number of psychometric instruments have been developed for the purpose of measuring style, the CSI emerged as the only psychometric measure to offer evidence satisfying each of the minimum criteria set by an influential critical review of the field (Coffield et al., 2004). These criteria included internal consistency, test-retest reliability, construct validity and predictive validity. Using the intuition-analysis dimension of style, the CSI categorizes individuals as analysts, characterized by systematic, sequential and logical reasoning, or intuitives, who favor a more innovative, creative and wholistic approach. On the basis that these characteristic differences in cognitive style reflect differences in underlying cognitive function, there exists potential to validate the

construct using neurological biomarkers and patterns of perceptual processing (Bendall, Galpin, et al., 2016).

Whilst Allinson and Hayes' (1996) CSI, Epstein's (1990) Rational/Experiential thinking and Kanheman's (2011) Systems of thinking all focus on the distinction between intuitive and analytical processing, Epstein and Kahneman are both dual-process theories, proposing intuition and analysis as two separate, parallel, but interacting processing modes. Rather than dual-processes, the CSI measures intuition-analysis as a single unidimensional bipolar construct. The debate regarding the comparative value of multi- and unidimensional construct measures is considered by Hodgkinson and Sadler-Smith (2003) and Hodgkinson et al. (2009), who, although noting limitations with both multi- and unidimensional construct measures, favor a multidimensional approach. Hayes, Allinson, Hudson, and Keasey (2003) however maintain that the unitary approach they adopt as the basis of the CSI is theoretically and empirically defensible and aligns with the approach adopted by a number of conceptual models of cognitive style.

1.2. Eye movements and cognitive style

Observing how an individual deploys their attention whilst locating a visual target (i.e., visual search) offers insight into the underlying cognitive processes involved as the search progresses (Bendall & Thompson, 2015; Galpin & Underwood, 2005). Tracking eye-movements is perhaps one of the most comprehensive ways to capture the dynamics of attention, offering the potential to reveal style-related cognitive processing (Bendall, Galpin, et al., 2016). Whilst the authors were unable to locate published studies directly examining the intuition-analysis dimension, individual differences in eye-movements have been noted for other proposed dimensions of cognitive style. For instance, visualizers have been found to attend more to pictorial information, whilst verbalizers prioritize written text (Koć-Januchta, Höffler, Thoma, Prechtel, & Leutner, 2017; Tsianos, Germanakos, Lekkas, Mourlas, & Samaras, 2009). In a further study tracking eye-movements, field-dependent (wholistic/global processing) and field-independent (analytical/local processing) styles were reported as influencing the allocation of attention to different visual elements (Mawad, Trías, Giménez, Maiche, & Ares, 2015). Although these attentional preferences indicate distinctions in the allocation of attention, they do not directly evidence the existence of specific style-related strategies for perceptual processing. Assessing the moment-by-moment pattern of eye-movements during visual search tasks is likely to provide a greater understanding of how style directs and guides perceptual behaviors (Henderson, 2003).

Nisiforou and Laghos (2016) suggested that, compared to field-independent individuals (analytical/local processing), those who favored a field-dependent style (wholistic/global processing) displayed a more disorganized visual search strategy represented by a substantially higher number of fixations and saccades. Nitzan-Tamar, Kramarski, and Vakil (2016) examined style-related visual search strategies based on the wholist-analytic dimension (Riding, 1991), a dimension that arguably shares many common characteristics with the intuition-analysis dimension of style (Sadler-Smith & Badger, 1998). Recording dwell time (total number of fixations and saccades in an area of interest) and number of transitions between images to make style-related comparisons across a series of global and local visual search tasks revealed that analysts were characterized by longer dwell times on both global and local processing tasks and, overall, made more transitions between images. Conversely, wholists seemed better able to adapt their preferred search strategy to fit the task requirements as no differences in response times or accuracy between global and local tasks were reported. However, because eye-movement data was gathered using the same visual stimuli that constitute the Extended Cognitive Styles Analysis Test (Peterson, Deary, & Austin, 2003), and which was used to define the participants' cognitive style along the wholist-analyst dimension, interpreting the findings in terms of indicative style-related

cognitive processing is problematic; any differences in eye-movements may not be indicative of style-related differences but rather a simple artifact of the task which was developed with the express purpose of delineating style along the specified dimension.

In an attempt to address the suggested limitations identified with Nitzan-Tamar et al.'s (2016) design, the present study uses the CSI as an independent style measure, free from the constraints of ability, against a separate and independent comparative visual search task (CVS). The CVS task requires participants to identify differences between pairs of simultaneously presented images, similar to a 'spot-the-difference' task (Galpin & Underwood, 2005; Pomplun et al., 2001). Critically, existing studies report that participants can approach this task with different cognitive strategies, focusing either on encoding details into memory, evidenced by making fewer comparison eye-movements, or reduce memory load by favoring a more dynamic between-images perceptual comparative strategy with increased comparison eye-movements (Hardiess & Mallot, 2015). Thus, the task was selected as a suitable means of investigating cognitive style strategies revealed through observed differences in eye-movements.

1.3. A neurological perspective and cognitive style

In a further effort to validate the intuition-analysis dimension of cognitive style—and associated CSI measure—using triangulated data sources, functional neuroimaging methods were also employed to identify potential neural mechanisms of style-related behavior. Investigating neural correlates of human visual attention using brain imaging techniques is common in attention resource allocation studies which have successfully identified functional connectivity and neural networking associated with visual orientation tasks (e.g. Corbetta & Shulman, 2002). The intuition-analysis dimension, as defined within the context of the CSI, is based partly on the—now questionable—assumption of hemispheric lateralization (Allinson & Hayes, 1996). That is, analysts are thought to be left-brain dominant, favoring logical and sequential processing, whilst intuitives utilize right hemispheric function (spatial orientation and visual comprehension) (Genovese, 2005). Despite a lack of evidence supporting the notion of cerebral dominance in the governing of cognitive processes (Hervé, Zago, Petit, Mazoyer, & Tzourio-Mazoyer, 2013; Lindell, 2011), the functional anatomy of the brain does offer the potential for processing preferences of intuitive and analytic thinkers to manifest in specific identifiable patterns of neural activation.

To date, few studies of cognitive style have attempted to identify style-related neural activity in conjunction with behavioral strategies. Neuroscientific evidence does however exist suggesting that cognitive style influences demands on specific brain structures. Greater activation in the fusiform gyrus (implicated in encoding of pictorial imagery) is reported for visualizers, whilst verbalizers show increased activation in the supramarginal gyrus (responsible for phonological encoding), a difference that is maintained even when presented with a mismatched stimulus (Kraemer, Rosenberg, & Thompson-Schill, 2009). Further evidence of style-structure dependence is presented by Walter and Dassonville (2007) who identified distinct regions of the parietal cortex that specifically process contextually embedded stimuli, suggesting that field dependent-independent styles may naturally exploit different neurological mechanisms.

Nevertheless, studies focusing on the neurophysiological characteristics of intuitive and analytic styles remain scarce. Using pupil diameter as an index of neural gain (described as an excitation/inhibition-contrast amplifier of neural communication and modulated by the locus coeruleus-norepinephrine system in the brain) Eldar, Cohen, and Niv (2013) reported style-related differences according to the sensing-intuitive dimension of the Index of Learning Style (Felder & Spurlin, 2005). Sensing style involves perceptual fact-based concrete learning, (e.g., visual features) and intuitive style is semantic meaning-based learning involving abstract concepts (e.g., semantic categories).

When neural gain was high participants showed a stronger inclination towards their preferred style; when gain was low, this inclination was weakened. Eldar et al. (2013) concluded that participants' predisposition for learning is modulated by neural gain and because learning style was less evident when neural gain was high, there is less cognitive flexibility under stress so learning is more strongly constrained by preferred learning style, resulting in diminished performance in some tasks requiring cognitive flexibility. Riding, Glass, Butler, and Pleydell-Pearce (1997) explored neural activations of the wholist-analytic dimension of style, as measured using the Cognitive Style Analysis Test (Riding, 1991). Using electroencephalography, neural impulses were recorded during a cognitive task involving both analytic and verbal processing. Viewing words presented on a computer screen at varying processing difficulties (i.e., speed of presentation), participants were required to respond when the stimuli belonged to a particular semantic category (e.g., fruit). Analysts produced significantly greater neural responses across all levels of processing difficulty, suggesting that analysts engage in more intensive cognitive processing irrespective of task complexity. Riding et al. (1997) did not monitor behavioral performance responses, so it is not possible to establish whether these differences in neural activity were associated with differences in performance, such as accuracy. Thus, the need remains to explore how any neurological differences recorded translate into intuitive-analyst style-related behavior.

1.4. The present study

The aim of the present study is to explore the psychophysiological correlates of the intuition-analysis dimension of cognitive style, as measured by the CSI. Using a unique methodological approach involving data triangulation, functional neuroimaging and eye-tracking techniques are employed alongside psychometric and performance measures. Hemodynamic responses in the PFC are recorded whilst simultaneously monitoring visual search strategies during a CVS task allowing style-related behavioral strategies to be associated with related neural mechanisms.

Functional near-infrared spectroscopy (fNIRS) is a non-invasive neuroimaging technique already successfully applied in the study of cognitive processes (Bendall, Eachus, & Thompson, 2016; Masataka, Perlovsky, & Hiraki, 2015). This technique, like functional magnetic resonance imaging (fMRI), is based on the principle of neurovascular coupling which details the relationship between cerebral blood flow and neural activation (Villringer & Dirnagl, 1995). fNIRS infers activity by measuring fluctuations in levels of oxygenated hemoglobin (oxy-Hb) and deoxygenated hemoglobin (deoxy-Hb) and these signals have been shown to be correlated with the blood oxygenation level-dependent (BOLD) response observed in fMRI (Cui, Bray, Bryant, Glover, & Reiss, 2011). Previous studies employing neuroimaging have provided evidence supporting PFC activation during cognitive task completion (e.g. Bendall & Thompson, 2016; Racz, Mulki, Nagy, & Eke, 2017) and the PFC has been shown to play an important role in cognitive control (Miller & Cohen, 2001). Using fNIRS, Racz et al. (2017) reported a strong response throughout the PFC during completion of a pattern-recognition test—compared to resting state—demonstrating that cognitive challenge increased activation in the PFC and indicating the potential value of adopting fNIRS in imaging the PFC in studies of cognitive function.

The task chosen for this study is the comparative visual search task. Searching within the environment is a complex behavior common to both human and non-human animals that involves a series of processes including allocation of attention and memory of the visual scene. Consequently, visual search has provided a platform for investigating both visual and cognitive function. Selective attention is the cognitive process that allows specific information from the environment to be selected and prioritized for further processing over less important or relevant stimuli. The processing of information may be either top-down,

characterized by internally generated, goal-directed behavior (e.g., a visual search guided by selected features), or bottom-up, the externally generated, automatic processing of information in the environment regardless of task demand (Itti & Koch, 2000). Working memory, essential for higher cognitive functions such as planning and decision making, is the ability to hold, recall and manipulate information for use in the short term (Baddeley, 2003). Both attention (Panieri & Gregoriou, 2017; Miller & Cohen, 2001) and working memory (Funahashi, Bruce, & Goldman-Rakic, 1989)—fundamental facets of information processing and therefore cognitive style—have been found to have neural correlates within the PFC, particularly the dorsolateral prefrontal cortex (dlPFC). Consequently, if as previous studies have suggested (e.g., Riding et al., 1997) intuitives and analysts differ in their strategies for performing visual search tasks similar to that used in the present study, it is anticipated that this difference will be reflected in activity of PFC as measured by fNIRS.

Both theoretical and conceptual accounts and empirical evidence exploring cognitive style suggest observable style-dependent differences in visual search strategies. As such, we selected eye-tracking measures that would capture these potential differences by measuring how often comparisons were made, and how far search moved between each subsequent fixation. Standard measures of number of saccades and fixation duration were also captured. These are useful because in the CVS task, there is an increased demand on encoding into working memory which may be reflected by increased fixation duration. This in turn may reduce the strength of the relationship between number of saccades and response time in comparison to a standard visual search task. Whilst the available evidence is limited, somewhat contradictory, and in some cases only relates indirectly to the intuitive-analytic dimension, it was anticipated that, as suggested by the earlier work of Nisiforou and Laghos (2016) and conceptualizations of style offered by Allinson and Hayes (1996), Epstein (1990), and Kanheman (2011), participants identified by the CSI as analytic will exhibit a more organized and systematic visual search strategy, with fewer eye-movements, than those participants identified as intuitive. In addition, given the neural mechanisms underlying cognitive processes, it is anticipated that the intuition-analysis dimension will be reflected in observable variations and differentiated patterns of style-dependent neurological activation representative of associated cognitive workload indexed by increased activation for analysts compared to intuitives as reported by Riding et al. (1997) and according to conceptual accounts associating an analytic style with effortful, deliberate, rule-driven processing (Epstein et al., 1996; Hodgkinson et al., 2009; Kahneman, 2002; Kahneman & Frederick, 2002; Tay et al., 2016). Behavioral performance data, including response time and task accuracy were also collected, enabling interactions between style-preference, task performance and psychophysiological response to be explored.

2. Method

2.1. Design

A quasi-experimental between-subjects design was used to examine neural and behavioral correlates of the intuition-analysis dimension of cognitive style. The independent variable was cognitive style (intuitive or analytic) as defined by the CSI (Allinson & Hayes, 1996, 2012). The three dependent variables studied were evoked brain activation represented by changes in oxy-Hb using fNIRS, visual search strategy captured using eye-tracking and represented by fixation duration, number of saccades, proportion of comparative saccades, and distance moved, and finally behavioral performance measures of accuracy score (percentage correct) and task related response time (seconds) on the CVS task.

2.2. Participants

The initial study sample included 56 university staff and students (45 female, 11 male) aged between 18 and 57 years ($M = 28.53$, $SD = 9.48$). For the purposes of comparative analysis, participants were assigned to either an intuitive group ($n = 16$, mean age 30.25, $SD = 11.12$, mean CSI score 31.19, $SD = 5.89$) or an analytic group ($n = 31$, mean age 28.0, $SD = 9.38$, mean CSI score 54.42, $SD = 7.23$) based on their CSI score indicating a 'pure'/'tendency towards' either intuition or analysis (Allinson & Hayes, 2012; see Materials and Apparatus section for further details). The remaining nine participants fell in the Adaptive category, meaning that their CSI scores did not confer an analytic or intuitive cognitive style. These participants were excluded from comparative analyses but included in correlational analyses. Ethical approval was gained from the School of Health Sciences' Ethics Panel at the University of Salford (HSRC12-88). All participants received an inconvenience allowance of £10.

2.3. Materials and apparatus

2.3.1. The cognitive style index (CSI)

The CSI is a 38 item self-report psychometric measure used to determine preferred cognitive style along the intuition-analysis dimension (Allinson & Hayes, 1996). Participants respond *true*, *uncertain*, or *false* along a 3-point Likert scale to statements such as '*to solve a problem I have to study each part of it in detail*'. Each statement attracts a score of 0, 1 or 2 according to the selected response and by applying reverse scoring guidelines to 17 items. A total scale score is achieved by summing responses to all 38 items. The CSI has a theoretical range of 0–76, with lower scores indicative of intuitive style and higher scores indicative of analytic style. Extreme scores represent 'pure' style preferences; scores in the range 0–28 represent intuitive style and in the range 53–76 analytic style. Moderate scores, in the range 29–38 and 46–52 respectively, represent quasi-intuitive and quasi-analytic style groupings reflecting a tendency towards, but not full adoption of, that style category. Centralized scores, 39–45, represent an adaptive style (Allinson & Hayes, 2012). For the purposes of the study and to optimize comparative data analysis, CSI pure and quasi style groupings were combined to form single intuitive (i.e., scores 0–38) and analytic (scores 46–76) groups. Participants exhibiting an adaptive style (39–45) were excluded from comparative analysis but were included for correlational analysis.

2.3.2. Comparative visual search task

The experimental task comprised 20 randomized CVS trials presenting pairs of images in parallel. In half the trials the pairs of images were identical and in half there existed subtle differences. Images depicted a variety of real-world scenes selected from a larger stimulus set previously reported in Galpin, Underwood, and Chapman (2008). Differences were created using Photoshop to manipulate images so that some objects were deleted, in part or in full, moved, or had their color or orientation changed and pre-tests ensured that differences were not immediately obvious but were clear once were pointed out (Galpin et al., 2008; Fig. 1). The objective of the task was to identify if a difference existed between each pair of images.

2.3.2.1. Eye-tracking. A Tobii T120 eye-tracker (Tobii Pro), which emits infrared light to monitor and track eye movements, gathered data at a frequency of 120 Hz with a spatial resolution of 0.2°. Tobii Studio software was used to record eye movement data (Tobii Pro).

In order to assess differences in visual search strategies across cognitive style groups, average fixation duration and the number of saccades were computed as indices of engagement in direct encoding and number of steps involved in visual processing (Galpin &

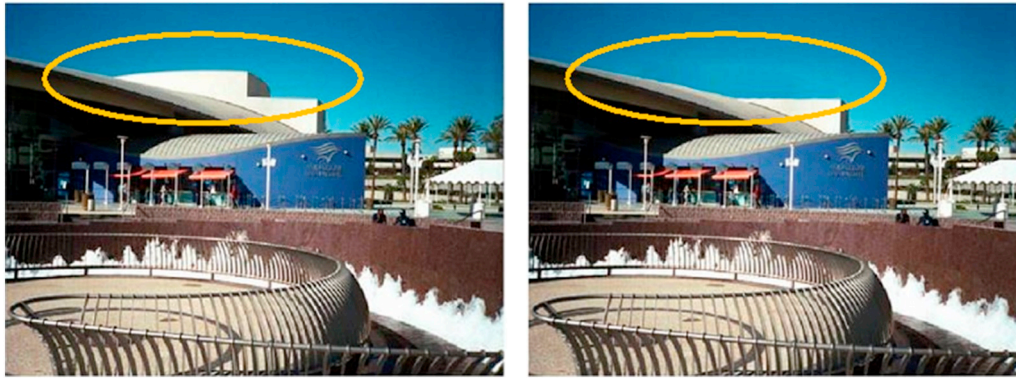


Fig. 1. Example stimuli for a difference trial on the CVS task.

Underwood, 2005; Pomplun et al., 2001). A systematic point-by-point strategy, represented by shorter fixations and a higher proportion of comparative saccades, prioritizes a reduced memory load over high-encoding behaviors. Longer fixations and fewer comparative saccades represents greater engagement in direct encoding. The variable distance moved from corresponding points on the image pair was calculated to establish how focused or dispersed the search was (Galpin & Underwood, 2005). The measure was computed by subtracting the distance between the two corresponding points on each image from the horizontal x-coordinate of all fixations on the right hand image. This essentially allows the second image to be mapped onto the first, providing an indication of how far saccades on the second image were directed away from the corresponding point on the first image. A smaller distance moved signifies a more targeted visual search indicative of an analytic scan strategy, whilst a greater distance moved would indicate the use of an intuitive scan strategy.

2.3.3. Functional near-infrared spectroscopy

An fNIR Imager 1000 (Biopac Systems Inc.) was used to record changes in hemodynamic activity in the PFC using Cognitive Optical Brain Imaging Studio data collection suite (fNIR Devices, LLC). This system has a temporal resolution of 500 ms (2 Hz) and detects concentration changes in cerebral blood flow using infrared light to monitor levels of oxy-Hb and deoxy-Hb within the PFC via a continuous wave 16 channel probe secured across the forehead. The probe was aligned to Fp1 and Fp2 of the international 10–20 system (Jasper, 1958), with Fpz corresponding to the midpoint of the probe (Ayaz, Izzetoglu, Shewokis, & Onaral, 2010). Data were analyzed offline using fnirSoft (Ayaz, 2010). Raw data were processed with a finite impulse response linear phase low-pass filter, with order 20 and cut-off frequency of 0.1 Hz, to attenuate high frequency noise, respiration and cardiac effects. A sliding-window motion artifact rejection algorithm and visual inspection of the data was used to remove motion artifacts and saturated channels (see Ayaz et al., 2010 for a detailed description of these methods). Oxy-Hb was then calculated using the modified Beer-Lambert Law (Sassaroli & Fantini, 2004). To allow for comparative analysis, task-related data was extracted for hemispheric regions of interest, with channels 3, 4, 5 and 6 representing the left dlPFC and channels 11, 12 13 and 14 representing right dlPFC activity (Fig. 2). Synchronized markers were scheduled to enable extraction of baseline neural activity (5s) and to identify the beginning and end of the experimental task. Task-related evoked activity was then compared with baseline activity and across style groups using mixed analysis of variance (ANOVA).

2.4. Procedure

Once participants had provided informed consent and data relating to handedness, age, gender and ethnic group had been recorded, the

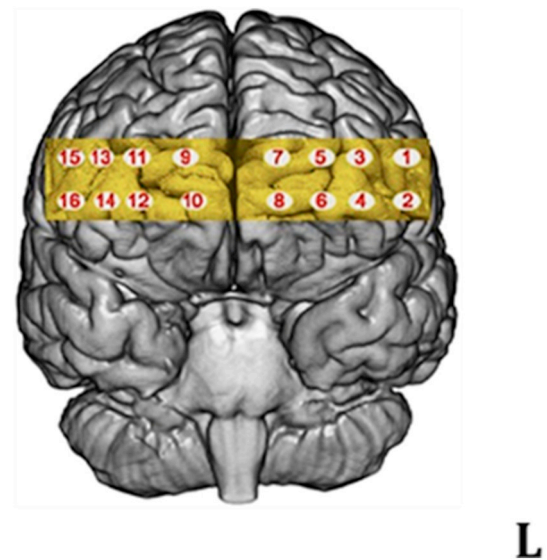


Fig. 2. Positioning of the fNIRS channels across the PFC.

fNIRS headband was positioned on the participant's forehead and secured using elastic strapping. Baseline brain activation was then recorded whilst the participant was at rest. For the purposes of task completion and to enable eye tracking, participants were seated at a distance of 70 cm from a computer monitor, placing their chin on a chin rest to minimize head movement during the task. A nine-point eye calibration procedure aligning gaze with the eye tracker was conducted with all participants in advance of task initiation. Following successful calibration the CVS task began. Each trial involved the presentation of a pair of images on the computer screen. Stimuli were presented using E-Prime version 2.0 (Psychological Software Tools, Inc.) on a 36 cm × 27 cm computer monitor with a resolution of 1024 × 768 pixels. Participants were required to indicate whether they believed the two images were identical or were different in some way by pressing one of two keys on the keyboard ('Q' = identical, 'P' = different). Participants were advised that the task was not time-limited but that they should endeavor to respond as soon as they were confident that their response was accurate. Four practice trials preceded the experimental trials. Feedback on correct answers and response time was given between each trial. Pressing one of the response keys triggered presentation of the next image pair. In addition to neuroimaging of brain activation and tracking eye-movements, response times (RT) and accuracy scores (percentage of correct responses) were recorded during task completion. To ensure participants were blind to the nature of the study, the CSI was administered once the task had been completed.

2.5. Analytical approach

Due to advantages of reporting both Bayesian analyses and traditional null hypothesis significance tests (NHST; Quintana & Williams, 2018), we report both analyses below. NHST and Bayesian statistical analyses were conducted using JASP (JASP Team, 2017). Bayes factors (BF) are calculated on distributions of effect size to provide the relative probability of observed data between competing statistical hypotheses; the null hypothesis (H0) and the alternative hypothesis (H1). See Jarosz and Wiley (2014) for an introduction to Bayesian statistics. BFs are expressed as the probability of the data given H1 relative to H0. Values larger than 1 provide evidence for H1, whilst values below 1 provide support for H0.

3. Results

One participant was excluded from all analyses due to limited engagement with the experimental task reflected by a low accuracy score (35%) and a high percentage of false positive responses (80%). A further participant was excluded from the analytic group for RT analyses as responses exceeded the threshold of three standard deviations from the mean. Due to technical malfunction 15 datasets were excluded from eye-movement analysis. Fixations of less than 100 milliseconds were also eliminated from analysis (see Galpin & Underwood, 2005). Additionally, owing to neuroimaging software malfunction, 4 datasets (3 analytic, 1 intuitive) were excluded from fNIRS data analysis. All raw data is available at Bendall, Lambert, Galpin, Marrow, and Cassidy (in prep).

3.1. Behavioral performance analysis

Behavioral data was analyzed using traditional NHST independent *t*-tests, Pearson correlations and the Bayesian equivalents, to examine group differences and relationships in task performance presented in Table 1 and Fig. 3. Because of the different sample sizes in each group, Hedge's *g*, which weights effects size according to relative sample size, was calculated to express effect sizes in NHST analyses. All Bayesian analyses were conducted using default priors. Accuracy scores did not differ significantly between groups, $t(40) = 0.77, p = .44, g = 0.298$. Bayesian analysis produced a BF_{10} of 0.401 providing anecdotal evidence in support of the null hypothesis. Correlational analyses demonstrated that CSI scores were not correlated with accuracy, $r(45) = 0.096, p = .520$. Bayesian analysis produced a BF_{10} of 0.222 providing moderate evidence in support of the null hypothesis. Analysis of RT data revealed significantly faster response times for analysts, compared with intuitives, both when analysis was based on all trials, $t(39) = -2.34, p = .025, g = 0.769$ and when based on correct response trials only, $t(39) = -2.24, p = .031, g = 0.738$. Corresponding BFs of 2.532 (all trials), and 2.161 (correct trials), provide anecdotal support for the alternative hypothesis, where the data are 2.532 and 2.161 times more likely to be observed under the alternative hypothesis.

Correlational analyses demonstrated that CSI scores were correlated with RT, $r(45) = -0.435, p = .001$; Fig. 4, and RT for correct trials only, $r(45) = -0.424, p = .002$; Fig. 5. Bayesian analyses produced corresponding BF_{10} s of 16.978 and 12.973 providing strong evidence in

Table 1

Summary statistics for style-based group differences in task performance measures.

	Accuracy (%) Mean (SD)	RT (s) Mean (SD)	RT (s) correct responses Mean (SD)
Intuitive	71.07 (13.18)	22.91 (10.9)	22.29 (10.9)
Analytic	74.11 (11.39)	16.47 (6.76)	16.17 (6.61)

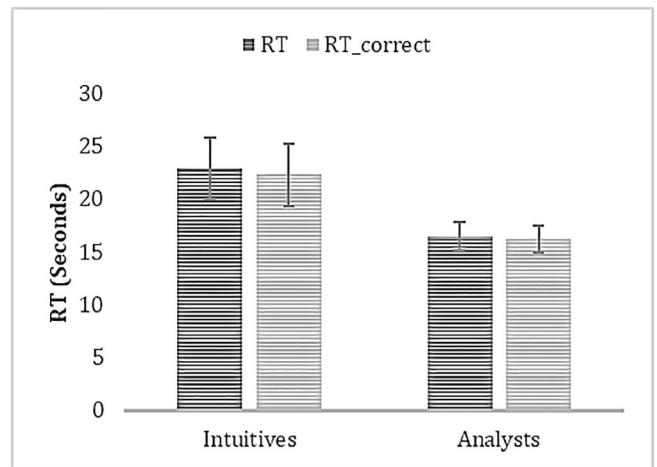


Fig. 3. Mean (± SEM) task response times (RT) to all trails and correct trials only for intuitive and analytic style groups.

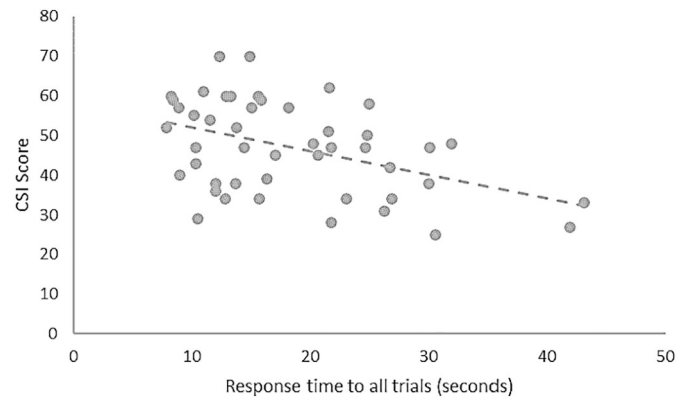


Fig. 4. Response time to all trials as a function of CSI score.

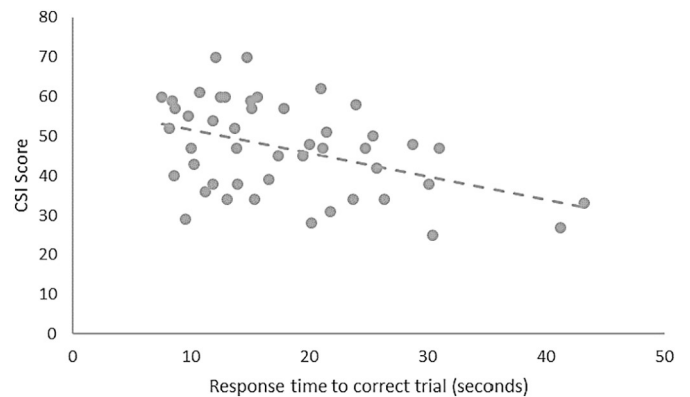


Fig. 5. Response time to correct trials as a function of CSI score.

support of the alternative hypothesis where individuals with a more analytic style were quicker at completing the CVS task.

3.2. Eye movement analysis

Fifteen data sets were lost due to technical issues with network communication between fNIRS hardware, the eye-tracking system and the experimental software. A further data set was lost due to poor calibration (substantial periods of unstable signal, and over 40% of fixations less than 100 ms). After removal of participants classed as Adaptive, the comparative eye-tracking analyses were therefore based on 36 data sets (24 analysts, 12 intuitives). Independent *t*-tests

Table 2
Summary statistics for style-based group differences in tracked eye-movement measures.

	Fixation duration (ms) Mean (SD)	No. saccades Mean (SD)	Proportion of comparative saccades (%) Mean (SD)	Distance moved (degrees) Mean (SD)
Intuitive	230 (23.8)	81.98 (31.9)	31.1 (7.3)	1.00 (17.1)
Analyst	228 (22.1)	61.01 (25.8)	31.0 (5.2)	1.05 (13.0)

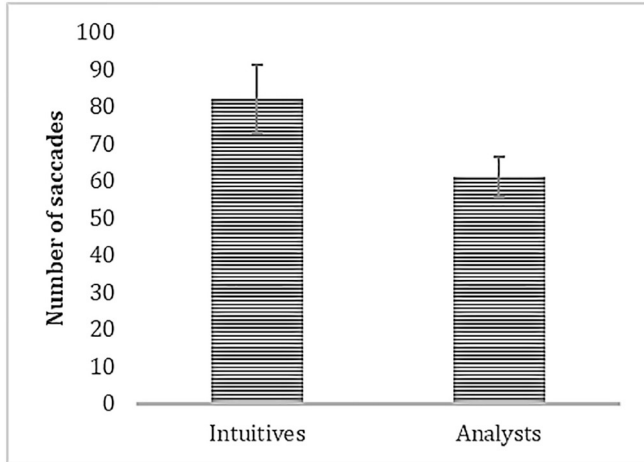


Fig. 6. Mean (± SEM) number of saccades for intuitive and analytic groups.

confirmed that average fixation duration, reflecting level of encoding, did not differ between intuitive and analytic groups, $t(34) = -0.217$, $p = .829$, $g = 0.088$. Corresponding Bayesian analysis produced a BF_{10} of 0.342 suggestive of anecdotal to moderate support for the null hypothesis. The intuitive group did employ a significantly greater number of saccades during their search compared to analysts, $t(34) = -2.12$, $p = .041$, $g = 0.75$; BF_{10} 1.785 (Table 2; Fig. 6). The number of saccades is reflective of task complexity and relative difficulty with which the visual search was completed. There were no style group differences between the proportion of comparative saccades, $t(34) = -0.023$, $p = .982$, $g = 0.008$; BF_{10} 0.336 (anecdotal to moderate support for the null hypothesis) or the distance moved from the corresponding point on the paired image $t(34) = 0.978$, $p = .335$, $g = 0.341$; BF_{10} 0.484 (anecdotal support for the null hypothesis).

Correlational analyses (based on 41 data sets, including the adaptives) between the eye tracking metrics and CSI scores supported the findings of the group comparisons, with the number of saccades being the only variable to return a significant relationship with style-preference, $r(41) = -0.436$, $p = .004$ (Fig. 7). That is, higher CSI scores, indicative of an analytic style, were associated with the use of fewer saccades during the comparative visual search task. The corresponding

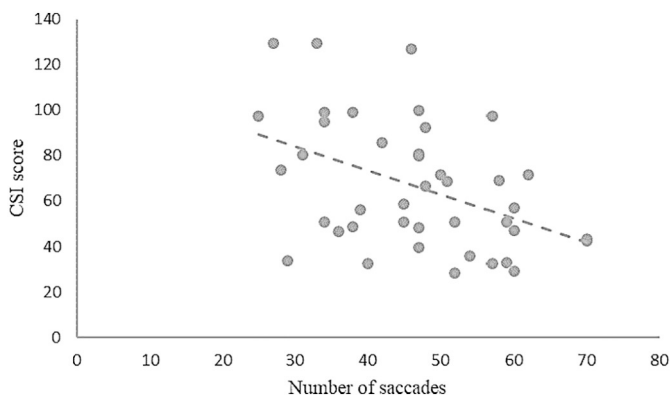


Fig. 7. Number of saccades as a function of CSI score.

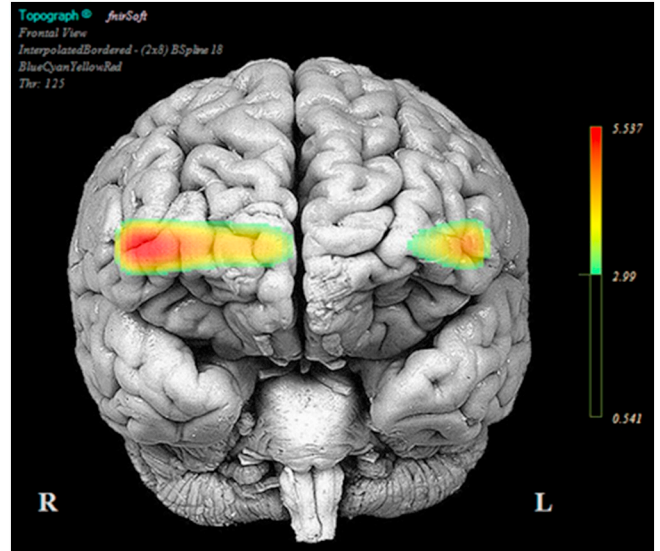


Fig. 8. Increased levels of oxy-Hb in the right-dIPFC.

Bayesian correlational analysis produced a BF_{10} of 9.794 suggesting that the data are 9.794 times more likely under the alternative hypothesis (Fig. 8).

3.3. fNIRS analysis

A 2 (style: intuitive vs. analytic) × 2 (task: baseline vs. CVS task) × 2 (hemisphere: left dIPFC vs. right dIPFC) mixed ANOVA was conducted to assess evoked hemispheric brain activation according to cognitive style preferences. A significant main effect was reported for task, $F(1, 40) = 85.47$, $p < .01$, $\eta^2 = 0.681$, demonstrating increased task-evoked neural activity compared to baseline. The corresponding Bayesian mixed ANOVA revealed a BF_{10} of $5.187e + 26$, indicating extreme evidence in support of the alternative hypothesis. There was also a significant effect of hemisphere on oxy-Hb, $F(1, 40) = 12.86$, $p = .001$, $\eta^2 = 0.243$, indicating greater activation in the right dIPFC (Fig. 6). However, Bayesian analysis revealed a BF_{10} of 0.562, indicating anecdotal evidence in support of the null hypothesis. There was no significant main effect for cognitive style, $F(1, 40) = 2.44$, $p = .126$, $\eta^2 = 0.057$, suggesting similar levels of neural activity across style groups. Here a BF_{10} of 0.380 suggests that the data are 2.632 times more likely under the null hypothesis and provide anecdotal support.

A significant task × hemisphere interaction effect was reported, $F(1, 40) = 12.86$, $p = .001$, $\eta^2 = 0.243$, reflecting greater right dIPFC activation during task completion (Fig. 6). This was supported by Bayesian analysis that produced a BF_{10} of 3.984 suggestive of moderate evidence in support of the alternative hypothesis. No significant interactions were reported between cognitive style and hemispheric activation or task-evoked activity (all $p > .05$). Correlation analyses suggest that CSI scores are not related to task-related neural activation for both regions of interest; left dIPFC $r(41) = 0.039$, $p = .788$; BF_{10} 0.183, right dIPFC $r(41) = 0.247$, $p = .084$; BF_{10} 0.756.

Individual fNIRS channel analysis was performed using 2 (style:

Table 3
Results of individual channel 2 (intuitive/analyst) × 2 (baseline/task) mixed ANOVAs and Bayesian analysis.

Channel	Mean (SD)		Main effects		Interaction effect	
	Analysts	Intuitives	Style grouping		Task × style	
			Task	Task	Task	Task
1	1.10 (1.35)	1.12 (1.68)	$F(1, 39) = 0.002, p = .963, \eta^2 = 0.000; BF 0.255$	$F(1, 39) = 21.16, p < .01, \eta^2 = 0.352; BF 16177.13$	$F(1, 39) = 0.002, p = .963, \eta^2 = 0.000; BF 0.384$	
2	4.39 (3.06)	3.81 (2.62)	$F(1, 37) = 0.343, p = .562, \eta^2 = 0.009; BF 0.289$	$F(1, 37) = 68.14, p < .01, \eta^2 = 0.648; BF 1.085e+12$	$F(1, 37) = 0.343, p = .562, \eta^2 = 0.009; BF 0.386$	
3	1.15 (1.58)	0.94 (2.24)	$F(1, 40) = 0.124, p = .727, \eta^2 = 0.003; BF 0.289$	$F(1, 40) = 12.23, p < .01, \eta^2 = 0.234; BF 266.62$	$F(1, 40) = 0.124, p = .727, \eta^2 = 0.003; BF 0.332$	
4	4.37 (2.49)	4.11 (2.28)	$F(1, 33) = 0.092, p = .764, \eta^2 = 0.003; BF 0.289$	$F(1, 33) = 102.1, p < .01, \eta^2 = 0.756; BF 3.669e+14$	$F(1, 33) = 0.092, p = .764, \eta^2 = 0.003; BF 0.289$	
5	1.27 (1.75)	0.98 (1.57)	$F(1, 30) = 0.212, p = .648, \eta^2 = 0.007; BF 0.321$	$F(1, 30) = 13.34, p < .01, \eta^2 = 0.308; BF 388.52$	$F(1, 30) = 0.212, p = .648, \eta^2 = 0.007; BF 0.386$	
6	2.64 (2.96)	1.84 (2.98)	$F(1, 37) = 0.630, p = .432, \eta^2 = 0.017; BF 0.327$	$F(1, 37) = 19.77, p < .01, \eta^2 = 0.348; BF 24949.77$	$F(1, 37) = 0.630, p = .432, \eta^2 = 0.017; BF 0.405$	
7	1.23 (2.23)	-0.19 (1.96)	$F(1, 38) = 3.99, p = .053, \eta^2 = 0.095; BF 0.898$	$F(1, 38) = 2.17, p = .149, \eta^2 = 0.054; BF 2.181$	$F(1, 38) = 3.99, p = .053, \eta^2 = 0.095; BF 2.39$	
8	2.15 (3.82)	1.32 (3.1)	$F(1, 35) = 0.448, p = .508, \eta^2 = 0.013; BF 0.331$	$F(1, 35) = 7.86, p < .01, \eta^2 = 0.183; BF 35.168$	$F(1, 35) = 0.448, p = .508, \eta^2 = 0.013; BF 0.434$	
9	0.99 (1.81)	0.15 (2.01)	$F(1, 38) = 1.76, p = .192, \eta^2 = 0.044; BF 0.480$	$F(1, 38) = 3.32, p = .08, \eta^2 = 0.08; BF 3.578$	$F(1, 38) = 1.76, p = .192, \eta^2 = 0.044; BF 0.844$	
10	4.21 (4.69)	2.7 (2.4)	$F(1, 32) = 1.01, p = .324, \eta^2 = 0.030; BF 0.377$	$F(1, 32) = 22.99, p < .01, \eta^2 = 0.396; BF 52373.12$	$F(1, 32) = 1.01, p = .324, \eta^2 = 0.030; BF 0.641$	
11	1.53 (1.74)	0.40 (1.6)	$F(1, 34) = 3.66, p = .064, \eta^2 = 0.097; BF 0.734$	$F(1, 34) = 10.78, p < .01, \eta^2 = 0.241; BF 282.06$	$F(1, 34) = 3.66, p = .064, \eta^2 = 0.097; BF 2.86$	
12	4.67 (2.48)	3.41 (2.23)	$F(1, 33) = 2.25, p = .143, \eta^2 = 0.064; BF 0.374$	$F(1, 33) = 92.31, p < .01, \eta^2 = 0.737; BF 4.108e+13$	$F(1, 33) = 2.25, p = .143, \eta^2 = 0.064; BF 1.10$	
13	1.12 (1.62)	0.05 (1.43)	$F(1, 30) = 3.51, p = .071, \eta^2 = 0.105; BF 0.807$	$F(1, 30) = 4.25, p = .048, \eta^2 = 0.124; BF 6.038$	$F(1, 30) = 3.51, p = .071, \eta^2 = 0.105; BF 2.08$	
14	5.94 (2.21)	5.13 (2.58)	$F(1, 34) = 0.945, p = .338, \eta^2 = 0.027; BF 0.302$	$F(1, 34) = 179.6, p < .01, \eta^2 = 0.841; BF 2.005e+21$	$F(1, 34) = 0.945, p = .338, \eta^2 = 0.027; BF 0.520$	
15	0.9 (1.17)	0.44 (1.61)	$F(1, 37) = 1.08, p = .306, \eta^2 = 0.028; BF 0.377$	$F(1, 37) = 8.95, p < .01, \eta^2 = 0.195; BF 74.722$	$F(1, 37) = 1.08, p = .306, \eta^2 = 0.028; BF 0.612$	
16	5.02 (2.03)	4.43 (3.05)	$F(1, 36) = 0.519, p = .476, \eta^2 = 0.014; BF 0.282$	$F(1, 36) = 131.5, p < .01, \eta^2 = 0.785; BF 5.629e+17$	$F(1, 36) = 0.519, p = .476, \eta^2 = 0.014; BF 0.416$	

* $p < .05$.
** $p < .01$.

intuitive vs. analytic) × 2 (task: baseline vs. CVS task) mixed ANOVAs. A significant main effect of task was observed across all but two channels; voxel 7 and voxel 9 (Table 3). There were no significant main effects of CSI style, or any significant interaction effects for CSI style × task for any of the 16 channels, indicating comparable levels of neural activation across style groups for both resting state and during task completion (Table 3). The corresponding Bayesian analysis for CSI style produced BF_{10} between 0.255 and 0.898 demonstrating anecdotal to moderate support for the null hypothesis (Table 3). The Bayesian analysis of task supports the NHST analysis. For channels 7 and 9 BF_{10} of 2.181 and 3.578 were observed providing anecdotal support for the alternative hypothesis. The remaining channels produced BF_{10} between 35.168 and 2.005e+21 demonstrating very strong – extreme evidence in support of the alternative hypothesis. For channels 7, 11, 12 and 13 the interaction between CSI group and task produced BF_{10} of 2.39, 2.86, 1.10 and 2.08 suggestive of anecdotal support of the alternative hypothesis.

4. Discussion

The present study explored psychophysiological indices of the intuition-analysis dimension of cognitive style as measured using the CSI (Allinson & Hayes, 1996). The aim was to gather evidence validating both the style dimension and its associated psychometric measure, increasing confidence in the construct's veracity and in a self-report approach to its measurement, assisting the continuation of cognitive style research and practice in applied areas. Participants completed a CVS task during which eye tracking and neuroimaging data were gathered simultaneously. Visual search strategies and neural activity—elucidated through eye tracking and fNIRS techniques—were considered against measures of task performance—RT and accuracy—so that the degree to which style-dependent differences in psychophysiological mechanisms and functional behaviors could be established along the intuition-analysis dimension of style.

RT task performance data showed that analysts responded significantly quicker than intuitives but without compromising accuracy, which was comparable across the two style groups. This result held for analysis based only on trials where a correct response was made, demonstrating that analysts reached decisions quicker than intuitives, at least on this particular experimental task. The finding seems at first contradictory when considered against Nitzan-Tamar et al. (2016), who reported faster response times for participants exhibiting the wholistic style (a style classification similar to intuitive style). However, Nitzan-Tamar et al. used the same visual search task (Cognitive Style Analysis Test) to both identify participants' style preferences and measure performance, bringing into question the value of the performance data as an independent measure separate from the style classification measure. By employing an independent visual search paradigm, distinct from the style preference assessment measure used, the present study is perhaps better able to attribute any differences in task performance to the functional characteristics associated with the extremes of the intuition-analysis dimension of cognitive style, and not purely artifacts of the task itself. Thus, quicker observed response times are interpreted here as representative of superior decision-making capability of analysts, at least on this particular CVS task. Equally, it may be that differences in decision-making thresholds indicate that—by virtue of the intentionally subtle nature of differences between pairs of images—the demands of the CVS task are more closely aligned with an analytical approach and therefore analytic style. Studies introducing multiple tasks into the experimental paradigm will help establish the true nature of style-dependent differences in performance, but task-related differences in performance reported here do provide some support for the intuition-analysis dimension of cognitive style.

Analysis of eye tracking data found that intuitives employed a greater number of saccades but similar fixation durations to analysts during the CVS task. As with results from response time analysis, these

findings fail to support Nitzan-Tamar et al. (2016), who reported that wholists' approach was characterized by both fewer saccades and shorter fixations. Once again, it is suggested that contradictory findings may reflect limitations in the design adopted by Nitzan-tamar et al. Previous studies using eye-tracking techniques do provide support for style-related differences in visual attention, but only on visualizer-verbaliser (Koc-Januchta et al., 2017; Tsianos et al., 2009) and field-dependent/field-independent (Mawad et al., 2015) dimensions. Nisiforou and Laghos (2016) report a higher number of fixations and saccades, representing a more disorganized visual search, for field-dependent individuals, a style characterized by wholist/global processing similar to intuitive style, compared to field-independent individuals, characterized by analytical/local processing similar to analytic style. Interestingly, aside from the number of saccades, none of our strategy measures, designed to capture differences in visual search, were influenced by cognitive style. Establishing that performance differences were solely predicted by a different number of overt shifts of attention between the intuitives and analysts is an interesting finding and suggests a number of avenues for future research. First, it is possible that our measures were not fine-grained enough to capture qualitative strategy differences. For instance, it could be possible that analysts made better predictions about where to start and direct search, leading them to the target more quickly. The design of our stimuli (using real-world scenes) did not allow us to systematically assess this, but this could be manipulated in future studies. Second, it could be possible that strategy differences are covert, influenced by what information is encoded during fixations, rather than the spatial and temporal allocation of the fixations themselves. Again, manipulating stimulus details such as the feature complexity of objects or type of target difference, may allow us to assess differences in encoding within fixations.

Neuroimaging data analysis revealed a significant main effect of task [vs. baseline], establishing the validity of the CVS task as a means of eliciting cognitive challenge. Increased PFC brain activation during task completion, compared with resting state, represented increased mental workload during task completion, underlining further the potential value of the PFC in studies of cognitive processing (Racz et al., 2017).

On the basis of findings from resource allocation studies and knowledge regarding the neural mechanisms underlying cognitive processing (e.g. Corbetta & Shulman, 2002), evidence from neuroimaging studies reporting cognitive style-brain structure dependence for both visualizers-verbalizers (Kraemer et al., 2009) and field dependent-independent dimensions (Walter & Dassonville, 2007), and the suggestion that analytic thinkers engage in more intensive cognitive processing (Riding et al., 1997), observable variations and differentiated patterns of style-dependent neurological activation were anticipated. However, contrary to evidence presented in relation to other style dimensions, no main effect of style or interaction effect for style \times task were reported, indicating that both baseline and task-evoked brain activation were similar for intuitives and analysts. A further suggestion that hemispheric lateralization underlies the functional expression of the intuitive-analysis dimension (Allinson & Hayes, 1996) was explored, but, whilst a main effect for hemisphere was reported, there were no style-related hemispheric interactions. The failure to provide evidence supporting style-related hemispheric lateralization is perhaps unsurprising given a general lack of evidence supporting cerebral dominance in other areas (Hervé et al., 2013; Lindell, 2011). Higher overall activation in the right hemisphere reported here is likely related to the visuospatial nature of the task (Genovese, 2005). However, some caution is perhaps needed regarding the interpretation of the differential left-right hemispheric activation. Whilst the NHST analysis revealed a significant difference in activation, where increased neural activity was reported in the right dlPFC ($p = .001$), the corresponding Bayesian analysis contradicted this result providing a BF_{10} of 0.562 suggestive of anecdotal support for the null hypothesis.

Individual fNIRS channel analyses did not reveal any identifiable

differences in neural activity between style-groupings and so is further evidence against style-related hemispheric lateralization, at least in terms of the intuition-analysis dimension. Again, however, some minor differences between the NHST and Bayesian analyses were evident. Here the NHST analyses suggested that there were no significant interactions for style grouping and hemispheric neural activation, whereas the corresponding Bayesian analysis produced anecdotal support of an interaction in voxels 7, 11, 12 and 13. Whilst fNIRS is relatively easy to administer, and can reduce discomfort to participants, it is limited in the depth to which changes in oxygenation can be detected, restricting investigation to the more superficial levels of the brain. The potential role in style related processing of deeper brain areas was not able to be investigated using this methodology. Whole brain neuroimaging techniques may prove enlightening for future studies.

5. Conclusion

Identifying and understanding fundamental individual differences in approach to information processing remains an important area of basic and applied psychological research. The conceptualization of individual differences in information processing as 'style' is appealing and the potential value of style construct measures, particularly psychometric measures, in applied areas including education, business, and management is high (see for example Koshevnikov et al., 2014). However, amidst a critical onslaught aimed especially at psychometric self-report style measurement (e.g., Coffield et al., 2004), the field has stalled somewhat. Reviewing cognitive psychology and neuroscience studies of individual differences in information processing, Koshevnikov et al. (2014) notes the failure of such studies to help conceptualize cognitive style. Adopting a triangulated approach involving data capture focused on key dimensions of human psychological functioning including brain activity, eye movement, self-report and task performance, the present study provides some evidence supporting the intuition-analysis dimension of cognitive style and the validity of the CSI (Allinson & Hayes, 1996) as a self-report measure of the dimension. Quicker response times and fewer saccades suggests that analysts reached decisions faster and found the task less challenging than did intuitives. Findings from behavioral and physiological measures suggest that analysts and intuitives may possess inherent differences in decision-making thresholds. Whilst monitoring of eye movements revealed that both style groupings adopted similar visual search strategies during the task, analysts were able to conduct a more efficient search, signified by fewer saccades and faster response times; analysts were able to reach a definitive conclusion sooner than intuitives and were able to do so without compromising accuracy. The absence of observable differences in neurological activation suggests that the quicker response times recorded for analysts were not a consequence of increased mental workload or hemispheric specificity. Further studies that explore different cognitive tasks are needed as are studies that address questions regarding construct dimensionality and the relative validity of unidimensional measures such as the CSI and multidimensional measures such as the Rational-Experiential Inventory (Epstein et al., 1996) and Cognitive Reflection Test (Frederick, 2005), perhaps alongside one another in similar multivariate designs used in the present study. However, though the nuances of style-related differences are important, they are less important here; that individuals assigned to cognitive style groups based purely on their responses to the CSI exhibited discernible differences in information processing is, it is argued, evidence supporting the intuition-analysis dimension of cognitive style and its associated psychometric measure, the CSI.

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