Exploring the Impact of Verbal-Imagery Cognitive Style on Web Search Behaviour and Mental Workload

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Cognitive style has been shown to influence users' interaction with search interfaces. However, as a fundamental dimension of cognitive styles, the relationship between the Verbal-Imagery (VI) cognitive style dimension and search behaviour has not been studied thoroughly, and it is not clear whether VI cognitive style can be used to inform search user interface design. We present a study (N=29), investigating how search behaviour and mental workload (MWL) changes relate to VI cognitive styles by examining participants' search behaviour across three increasingly complex tasks. MWL was subjectively rated by participants, and blood oxygenation changes in the prefrontal cortex were measured using functional near-infrared spectroscopy (fNIRS).

Our results revealed a significant difference between verbalisers and imagers in search behaviour. In particular, verbalisers preferred a Sporadic navigation style and adopted the Scanning strategy as they processed information, according to their viewing and bookmarking patterns, whereas imagers preferred the Structured navigation style and reading information in detail. The fNIRS data showed that verbalisers had significantly higher blood oxygenation in the prefrontal cortex when using the same search interface, suggesting a higher MWL than imagers. When based on task complexity bias, the search time significantly increased as task complexity increased, but there were no significant differences in search behaviours. Our study indicated that VI cognitive styles have a noticeable and stronger impact on users' searching behaviour and their MWL when interacting with the same interface than task complexity, which can be considered further in future search behaviour studies and search user interface design.

CCS Concepts: • **Human-centered computing → Empirical studies in interaction design**.

Additional Key Words and Phrases: Cognitive Style, Interactive Information Retrieval, Mental Workload, Human-Computer Interaction, fNIRS

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1 INTRODUCTION

Cognitive style has been shown to significantly affect users' behaviour when interacting with machines and software. Users generally have a better performance using interfaces that match their cognitive style (e.g. [9, 24, 27, 28, 74, 101, 105, 117]). As a stable attitude in individuals' cognition, cognitive style was first proposed in 1937 [4] and has been normatively defined as *"an individual's typical or habitual mode of problem-solving, thinking, perceiving, and remembering"* [67]. Since information searching tasks require individuals to plan their search process, think about how to access information sources, select the useful ones, and decide on how to complete the search process [100], it is fair to assume that cognitive style will have a noticeable impact on individuals' information-searching behaviours.

Early researchers in the cognitive style field defined a large number of style dimensions [41], such as "field-dependent (FD)" versus "field-independent (FI)" [113], "serialist" versus "holis" [75, 76], and "convergers" versus "divergers" [37]. Many of these dimensions have only been supported by a single study due to their unclear definition [41], raising questions as to their reliability and universality. Riding and Cheema [91] reorganised the dimensions of the cognitive style into two orthogonal principle dimensions: "wholist-analytic" (WA) and "verbaliser-imager" (VI), based on the similarity between dimensions defined in existing studies. These two dimensions have become fundamental cognitive style dimensions in subsequent research [23, 55]. *Wholists* prefer to handle tasks using a whole-part processing strategy while *analytics* prefer to separate the tasks into discrete parts for solving [25]. Individuals are classified as *verbalisers* or *imagers* based on their preference for memory information expression is text or mental image, respectively [91]. Based on these two dimensions, cognitive style has been widely studied as a personality factor in fields including education, computer science, and information science [38]. These studies highlighted the impact of cognitive style on users' interaction behaviours and tried to figure out how to make the system more effective by considering users' cognitive style (e.g. [18, 32, 105]).

In the area of interactive information retrieval (IIR) research, information-searching behaviour has been shown to be significantly influenced by personal characteristics, including age, mental models, and the expertise level in the search context [38, 71]. As an important personality indicator, cognitive style has been summarised as one of the three main factors that affect information-searching behaviour by O'Brien et al. [71] after a scoping review of 223 published articles on the topic of individual differences in information-seeking behaviour.

Existing studies have highlighted the importance of considering *the WA dimension* of cognitive style during search user interface design by examining search task performance (e.g., [20–22, 30, 31, 54]) and the user's eye movement patterns [61, 86, 114]. Wholists (FD) have been found to prefer having an overview of the task before introducing it in detailed sub-topics while the analytics (FI) prefer to understand each of the sub-topics and then generate the whole picture [21, 22, 30, 54]. The differences in the way people locate information in Web directories suggested that wholists (FD) need a clearer structure than analytics (FI) and the system should provide the wholists (FD) some guidance on how to restructure the information [21]. However, less attention has been paid to how *the VI dimension* of cognitive style affects searching behaviour [71], or whether it could be used to inform search user interface design [112]. From the few existing studies [34, 38, 51, 53, 54, 88], initial findings reported different searching behaviours between verbalisers and imagers in their information strategies, query reformulation behaviours, web navigation styles, and information processing approaches. These findings highlight the value of further studying the VI cognitive style dimension in IIR.

Another important factor that influences users' information-searching behaviour is task complexity [11, 17, 60], which has been defined as *"number of subtopics or facets, number of operations required, number of sources or items required, the indeterminate nature of the task and the cognitive complexity of the task"* [110]. Researchers indicate that the time of completing a task increases with its difficulty [33, 38], and participants tend to reformulate the queries more frequently while doing a more difficult task [68]. It has been shown that the searching strategies are different when perceiving different difficulty task difficulty levels [17, 54]. Although O'Brien et al. [71] highlighted that cognitive style may impact IR behaviour in different complexity-level tasks, and the related studies on the WA dimension showed that the impact of cognitive style on information-searching behaviour is more noticeable when participants face more difficult search tasks [86], there are limited studies that considered the interactive impact of task complexity and VI cognitive style [38]. The relationship between the VI cognitive style and search behaviour remains ambiguous.

The aim of this paper is to explore the impact of VI cognitive style on searching behaviour, using task complexity as a factor of analysis. Additionally, we investigated participants' mental workload (MWL) as they completed the search tasks, to see whether cognitive style affects the mental effort involved, which has not been studied before.

2 RELATED WORK

We present three key aspects in this section: 1) current cognitive style measurements, 2) the impact of VI cognitive style on Interactive Information Retrieval, and 3) VI cognitive style and MWL.

2.1 Cognitive Style Measurements

Numerous subjective measures have been developed for assessing an individual's cognitive style on the WA dimension but comparatively few measures have been developed for the VI dimension. In 1991, [93] adapted the Cognitive Style Analysis based on his and his colleagues' previous work [90, 91, 95–97] to address the shortcomings in existing WA measures and the lack of VI measurements. Cognitive Style Analysis is a widely used measure of cognitive style in the UK and European research institutions [89]. It measures both the participant's position on WA and VI dimensions by three subsets of questions. However, Peterson's team [80–82] and [89] questioned the validity of Cognitive Style Analysis, especially its VI dimension measure, due to concerns about the questions used and its internal consistency. [82] developed a new measure, the Verbal-Imagery Cognitive Style (VICS) test, to address the identified shortcomings in Cognitive Style Analysis. Based on [91], VI styles can be classified based on whether a person prefers to process received information vocally or through mental imagery. The VICS test follows the same basic design principle of the Cognitive Style Analysis's VI dimensions, where verbal-related tasks ask for the items' conceptual category whereas imagery-related tasks require the participants to generate mental images. VICS has two groups of stimuli corresponding to measure verbal versus imagery cognitive style. The stimuli in the verbal group ask the participants to judge whether the two items in one stimulus are man-made or natural. Compared with Cognitive Style Analysis which asks "whether the two items are the same type", this criterion is easier for participants to identify the semantic conceptual category to which the items belong. For the imagery stimuli, the VICS test needs the participants to compare two objects' sizes in real life, which has been proved by [70] to require mental image generation, rather than comparing colour in Cognitive Style Analysis. The items used for verbal-related statements are not the same as those used for imagery-related statements in Cognitive Style Analysis. The VICS test uses the same stimuli for both verbal and imagery tasks, keeping them similar to each other and improving the comparability of the two types of tasks. In addition, the VICS test displays each stimulus in both word and image format to reduce the impact of a single presentation mode on participants, such as Cognitive Style Analysis. The VICS test contains 116 stimuli for each type of task consist of 58 word-based stimuli and 58 image-based stimuli (see Fig. 1).

The assessment of cognitive style of the VICS test uses the ratio of the median response time to the verbal-type tasks to the median response time to the imagery-type tasks. Compared with the average response time in Cognitive Style Analysis, the median value could minimise the effect from outliers [82]. The VICS test has been successfully applied by numerous studies in VI cognitive style dimension classification [8, 44, 58, 98, 103, 106]. Considering that the VICS test makes up for some of the defects of the previous measures, we chose it as the cognitive assessment tool for our research.

2.2 The Impact of VI cognitive style on Interactive Information Retrieval

There are very few studies that have focused on how the VI dimension influences IIR. Kinley and colleagues [51, 53] proposed a model to describe web searching behaviour, where they summarised the behaviour into four aspects:

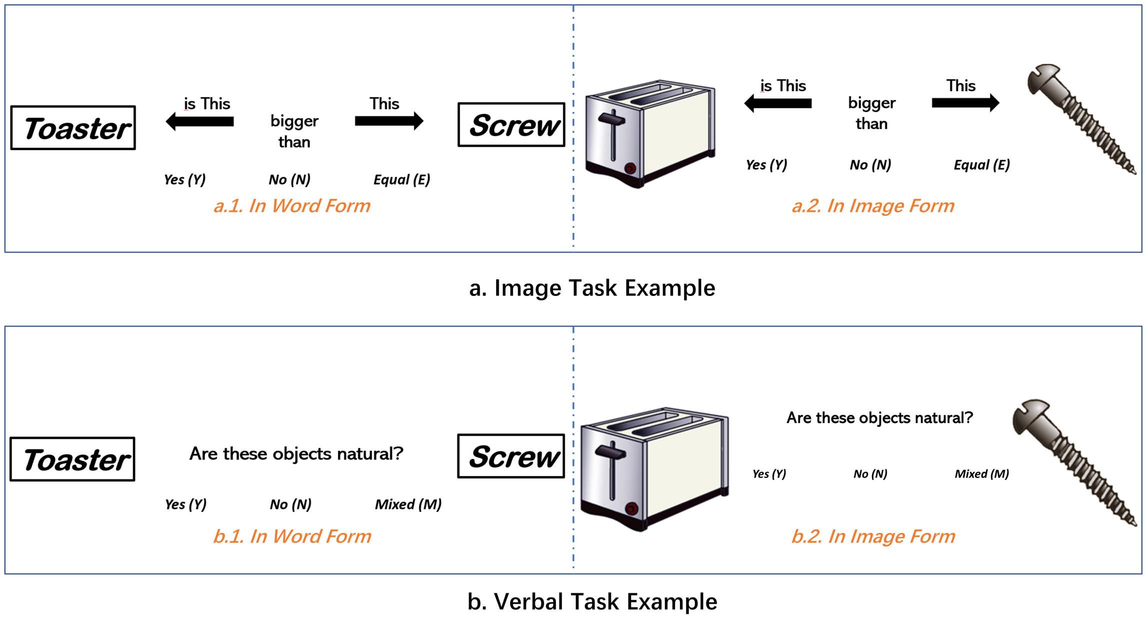


Fig. 1. Examples of the VICS test used in this study based upon Peterson et al.'s work [82]

Information Searching Strategy, *Query Reformulation Behaviour*, *Web Navigation Style*, and *Information Processing Approach*. Specifically, *Web Navigation Style* has been grouped into two types: *Sporadic* and *Structured*. *Sporadic* searchers prefer frequently reformulating queries depending on the first several search result descriptions whereas *Structured* searchers prefer to follow the search engine's systematic navigation steps. *Information Processing Approach* is classified into two groups: *Scanning* and *Reading*. *Scanning* searchers scan result pages quickly for general information, while *Reading* searchers read result pages in detail. Their results demonstrated that cognitive style significantly influenced users' *Web Navigation Style* and *Information Processing Approach*. Verbalisers preferred a *Sporadic* navigational style and *Scanning* strategy, while imagers adopted a *Structured* navigational style and *Reading* strategy [51, 53, 54]. One key limitation of their studies was the experiment setting. All the studies used three search tasks with different complexity levels and the participants were asked to complete the tasks in the same order (medium complexity level first, followed by the low complexity and then high complexity), which might create a learning effect and reduce the reliability of the results. In addition, although the search tasks used in the studies were set in different complexity levels, the researchers did not consider task complexity as an independent variable during their data analysis.

The result from Graff's study [34] was not in line with Kinley et al.'s findings [51, 53, 54]. Graff identified that verbalisers visited more pages in the hierarchical architecture whereas imagers visited more pages in the relational architecture in hypertext browsing strategies. Based on their definition of hierarchical and relational architecture, verbalisers tended to follow *Structured* navigation while imagers preferred *Sporadic* navigation. Participants in Graff's study [34] were asked to look at the information in a hypertext system to complete a series of questions at the end of the 10-minute session of browsing. The hypertext's information was organised in either a hierarchical or a relational architecture, participants were assigned to one of those two conditions. One possible reason that Graff reached a different conclusion from Kinley et al's studies is that they constrained the participants' way of gathering information in two specific ways but did not study them in a natural condition. Additionally, they did not consider the task complexity when designing the tasks.

Hariri and Maryam's finding [38] supports Graff's result, where they also found that the verbalisers adopted a *Reading* strategy whereas imagers showed a *Scanning* strategy. However, they did not detect a significant difference in search time or the visited pages between participants with different cognitive styles or on the task complexity bias. Their study highlighted that it is valuable to consider the cognitive style when designing the layout of the search engine.

Overall, current studies revealed that search behaviour can be influenced by cognitive style on the VI dimension, but do not have a consistent conclusion, which might be caused by the limited number of studies.

2.3 Cognitive style and MWL

Few studies have focused on how cognitive style influences participants' MWL on differently designed interfaces, especially on the VI dimension. [120] compared the MWL of participants in different groups of the WA dimension when they completed a shopping task with interfaces that adopted Virtual Reality (VR) and Augmented Reality (AR). The wholist participants showed a higher MWL when they used both interfaces than the analytic participants, but their MWL under the VR condition was comparatively lower than the AR condition. [2] used a multiplayer game to investigate whether cognitive style should be considered in interface design for team collaborative work. The interface used in their study was shown to have the lowest MWL and the best performance for the analytic-analytic team than the analytic-wholist and wholist-wholist teams.

In automotive research, the notification management system on in-vehicle devices was studied by [10]. They used a driving task as the primary task, and the notification management system was involved in the secondary task: picking up phone calls during driving. They found that the wholist participants had a higher MWL than the analytic participants. Each of the studies above indicates that the suitable interface for different cognitive style users is different. When the interface satisfies the users' cognitive style, their MWL could be lower.

Although there are not many cognitive style-MWL related studies, a number of studies have highlighted its effect on users' performance and behaviour in different human-machine communications, including user-authentication [12, 13, 28, 46–48], searching [18, 51, 62], e-learning [7, 32, 55, 105], online shopping [9, 24, 27, 101, 117, 118, 120], and gaming [3, 19, 85, 118]. For example, CAPTCHA preference and performance were affected by individuals' cognitive styles [12], different cognitive style readers had different searching and scanning strategies when they used electronic journals on mobile devices [18] and did the online shopping [24, 117], the students had a better learning performance when they used the e-learning system that fit their cognitive styles [55]. It has been proved that usability can be enhanced by matching interface design with a user's cognitive style [62, 87]. In addition, different interaction behaviours could require a different level of cognitive demands, which might induce different MWL [104]. Together, research results are clear that there is a relationship between cognitive style and MWL, although the nature of that relationship is still the subject of ongoing research.

3 EXPERIMENT DESIGN

This paper's aim is to explore how VI cognitive style influences users' performance and MWL during IIR. To examine these, we also consider task complexity as an interacting factor in the analysis. Our research questions (RQs) were:

a) Does cognitive style, on the VI dimension, have a noticeable effect on search behaviour?

b) Does mental workload during complex search differ by VI cognitive style?

To answer the RQs, we designed a between-subjects experiment where participants were asked to 1) complete three search tasks, and 2) take the VICS Test for cognitive style measurement. Cognitive style was used to break these participants into two groups, as per [53]. Search behaviour was examined through the number of viewed pages and bookmarked pages, similar to [72] and [119]. MWL was measured subjectively (ISA scale) and, same as [64], using a blood-oxygen brain scanner (fNIRS, described in Sec. 3.4.5) positioned over the Prefrontal Cortex (PFC).

3.1 Hypotheses

Six hypotheses were produced based on the RQs:

H1: VI cognitive style will influence search behaviour
H2: VI cognitive style will influence subjective MWL self-assessments during information searching
H3: VI cognitive style will lead to an observable difference in blood oxygenation in the PFC during information searching
H4: Task complexity will interact with VI cognitive style to affect users' search behaviour
H5: Task complexity will interact with VI cognitive style to affect users' subjective MWL ratings
H6: Task complexity will interact with VI cognitive style to affect users' blood oxygenation in the PFC.

H1 was based on the finding of [54], [34], and [38] that searchers with different cognitive styles behave differently during IIR. *H2* and *H3* were drawn from studies examining the relationship between cognitive style and MWL and performance (described in Section 2.3). Since we used only one search engine (Google Search) in this study and searchers with different cognitive styles adopted different search strategies, we assume that Google would be more supportive of one of the two cognitive styles. Therefore, searchers who were satisfied with Google would perform better and have a lower MWL, resulting in lower blood oxygenation in the PFC. H4, H5, and H6 were developed to examine whether the search task's complexity has an interactive impact with cognitive style on the searcher's behaviour and MWL.

3.2 Participants

30 participants (twenty males, ten females) with an average age of 25.2 were recruited to take part in the experiment. The participants were all students or staff from the School of Computer Science at the University of Nottingham. All participants had normal or corrected vision and reported no history of head trauma or brain damage. The study was approved by the university's ethics committee. Participants were provided with information about the study and their rights, and informed consent was gained before the study began. Participants received a £10 gift voucher as remuneration for their time.

3.3 Setup and Procedure

The experiment environment is shown in Fig. 2. There was a board between the participants and the researcher to reduce interference from the researcher's side to the participants. On the participant's side, there was a screen, a keyboard and a mouse for completing tasks, which was powered by a laptop on the researcher's side and mirrored its screen, therefore the researcher could clear the cache of each search task before the participants start the next one without disturbing them, and could make a log of the whole experiment. There was another laptop on the researcher's side for monitoring and recording participants' fNIRS signals. The start point and end point of each search task were

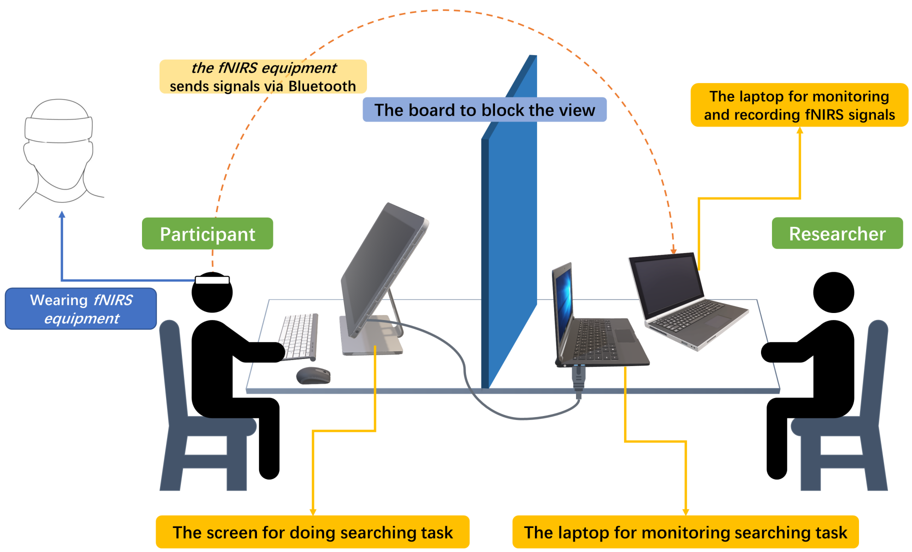


Fig. 2. Experiment Environment Set Up

recorded by this laptop using event keys (described further below). During the study, the order of search tasks and the two sections of the VICS test were designed based on Latin rotation to avoid learning effect and order effect [6].

Participants were first given example search tasks, such that they were ready to take part in the study, and provided with the details of the ISA scale on paper, describing the meaning of the five-point scale and how they should use it. The browser was set to Google's default search page at the beginning of each task, for the practice and the study. After placing the fNIRS equipment (*OctaMon*) carefully into position and checking for good sensor contact quality, participants were asked to relax for one minute to record baseline brain data. When they heard the prompt tone from the researcher, participants started to do the search tasks, which were provided on paper. While performing the search task (described in Sec. 3.4.1), they were asked to rate their workload in the past minute by saying a number from 1 to 5 according to the ISA scale when they heard the prompt tone every minute on the researcher's side. Compared with other response modes (e.g. entering a score into a phone), the "speak-out" method for recording ISA score has been proven to have a relatively low impact on workload (e.g., [1, 63, 66]). Similarly, research has shown that speaking aloud about a task does not significantly affect fNIRS measurements during tasks [83].

There were no constraints in terms of search behaviour and search time during the search tasks; they were asked to complete the tasks as they would normally. After completing a search task, participants were asked to again relax for one minute to re-establish a baseline reading and then started the next search task when the prompt tone was heard again. *Chrome* was used for search tasks, and after each task the cache was cleared. The search tasks stage lasted for around 45 minutes and all the search behaviours were screen recorded for subsequent analysis. The specific event keys recorded in this study are shown in Fig. 3. After finishing all three search tasks, we removed the fNIRS device and asked participants to fill in a "Task Familiarity" Likert scale. After around five minutes break, a VICS practice session was held before the formal VICS test was performed. [79] emphasised that the participants' familiarity with the language used in the VICS test can impact the results, which could affect their VI Cognitive Style classification. For example, verbalisers' response time might be increased because of the unfamiliarity with the words, resulting in a longer response time in the verbal section and being misclassified as imagers. As participants were either from the university's UK campus or in exchange from the Chinese campus, they were given the choice to take part either in English or Chinese (materials were prepared in both languages), such that they took part in a language they were fluent in. 9 participants took part in English and 21 in Chinese. The impact of this variable was assessed first in the analysis in Section 4. After completing the formal VICS test (around 15 minutes), the experiment ended.

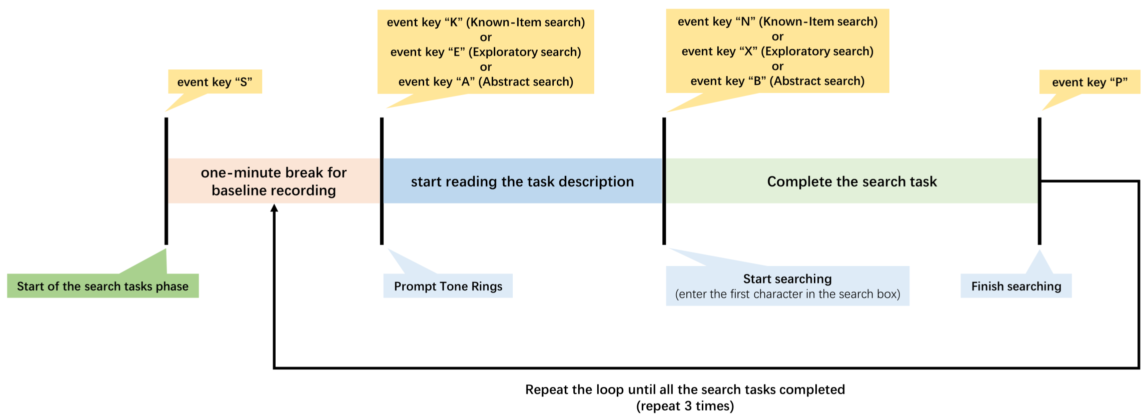


Fig. 3. Recorded event keys during the search task stage

3.4 Web Search Tasks

3.4.1 Task Design. The simulated work tasks used for this study were chosen as information-searching tasks. Although there are several different classifications of information-searching tasks (e.g., *Remember* versus *Analyse* versus *Create* [16]; *Factual* versus *Interpretive* versus *Exploratory* [49]; *Factual* versus *Exploratory* versus *Abstract* [54]), studies have typically followed a three-level complexity model developed by Bell and Ruthven [14] that groups search tasks according to the need for participants to make decisions and navigate. At level 1 (Simple), individuals can predict the needed information and the upcoming search process because the task provides the main search components and the focal point for the search process. They only need to make some decisions during the query. At level 2 (Medium), the searching process is less determinable and requires the user to be more engaged in decision-making and navigation. However the major search components are still clear to the searchers. In this type of task, individuals are expected to retrieve information from numerous websites. At the final level of the complexity model (Complex), the question only provides the searchers with a vague direction and they need to decide the important information, and how to evaluate the relevance of the result. In general, a simple level task is "a specific question with a specific answer" in that the searchers know exactly what information is needed, and how to assess the result's relevance; they only need to make some decisions during the query. A medium-complexity task is "a specific question with general answers" that requires more decisions on the query inputs and search process compared with a simple one. The most complex task is typically "a general question with general answers". We adopt these three levels in our study.

Following the information-searching task design principle [15], the content of the search tasks was designed relevant to the participant's daily life. As the range of the participants was designed as "students and staff at the University of Nottingham", the tasks were related to their vacation travel plans and their future career directions. Considering that it is challenging to find out whether the participants' search is completed when they are doing *Exploratory Searching* and *Abstract Searching* due to their open-ended searching results, the stop flag for these two search tasks has been designed as the number of the bookmarked web pages [49, 50]. Referring to the search tasks used in prior VI cognitive style studies [38, 54], one task was designed for each search task type:

- ***Known-Item Searching*** - *Assume that you are preparing to visit the Louvre Museum next week and you want to know the opening time of all the inside galleries. Please bookmark the web page on which you find the opening time of all galleries (not the opening time for the general Louvre Museum).*
- ***Exploratory Searching*** - *Assume that you are thinking about continuing doing PhD in the Human-Computer Interaction (HCI) area at the University of Nottingham. You decide to learn more about HCI PhD at the University of Nottingham. Please do the related searching and bookmark 5 to 8 web pages on which you can find useful information.*
- ***Abstract Searching*** - *Assume that you are planning to collect information related to your future career. Please bookmark 10 to 15 web pages on which you think you can find useful information related to getting a job and future career planning.*

3.4.2 Performance Data: Search Time. The time for completing each of the three search tasks was used to learn whether participants with different cognitive styles will have a significant difference in search time when facing the same search task. It is a widely used indicator for evaluating search performance (e.g. [38, 50, 73])

3.4.3 Behavioural Data: Number of Viewed Pages and Bookmarked Pages. We focused on *Web Navigation Style* and *Information Processing Approach* proposed by Kinley's team [51, 53, 54] in this study. Referring to their findings, *Sporadic* and *Scanning* searchers opened more web pages than *Structured* and *Reading* searchers. Instead of using the number of viewed web pages to represent the participants' web search behaviour and measure their search performance (e.g., [38, 50, 73]), we used the ratio of the number of bookmarked pages and viewed pages (BP/VP ratio). The required number for the bookmarked pages for each of the three search tasks in this study was controlled in a certain and small range, indicating the BP/VP ratio still mainly depends on the number of web pages that the participants viewed, *Sporadic* and *Scanning* searchers should have a lower BP/VP ratio than *Structured* and *Reading* searchers. Additionally, BP/VP ratio could determine the participants' search efficiency: the participants who bookmarked all the needed pages after viewing fewer web pages (higher BP/VP) could be interpreted to have a higher search efficiency.

3.4.4 Subjective MWL Measurement. The Instantaneous Self Assessment Workload Scale (ISA) was applied during the search tasks to measure the real-time workload of the participants, which is a widely used workload measurement technique that evaluates the participants' workload by asking them to rate their perceived workload every minute from 1 (low) to 5 (high) [45]. ISA was selected instead of e.g. NASA TLX [39], as NASA TLX is a) applied retrospectively after each task, b) time-consuming to apply per task, and c) creates significant changes in blood oxygenation in the PFC, which affects baseline measurements. For these reasons, NASA TLX was not a suitable fit for our methodology, whilst ISA provides several measurements per task.

3.4.5 fNIRS Data. Brain activity in the PFC has a well-established relationship with MWL [56]. Several brain sensing techniques have been widely used for MWL measure, including electroencephalography (EEG) [108], functional Magnetic Resonance Imaging (fMRI) [69], and functional Near Infrared Spectroscopy (fNIRS) [64, 65, 83]. EEG records electrophysiology of the cerebral cortex by placing electrodes over the participants' scalp, whereas fMRI and fNIRS reflect brain activity using its detected changes in blood flow [102]. fNIRS has been proven to be more robust to motion artefacts compared to EEG, and does not limit participant movement [78, 84] as fMRI does. Specifically, fNIRS signal has been highlighted as not being influenced by keyboard input and verbalisation artefact [65]. Therefore, we chose fNIRS for our study.

fNIRS data was collected by a non-invasive fNIRS headband *OctaMon* from Artinis Medical Systems[1], and recorded with the *OxySoft* software. *OctaMon* is a fNIRS continuous-wave device consisting of eight emitters and two detectors, placed on the participant's forehead, using wavelengths of 760 and 850 nm. Our configuration results in 6 long-distance channels with an inter-optode distance of 35 mm, and 2 short separation channels with an inter-optode distance of 10 mm. Short separation channels allow blood oxygenation changes in the skin to be subtracted from blood oxygenation in the brain. The data was recorded at a sampling frequency of 10 Hz. The optodes were positioned to cover the PFC area; the position is in reference to International EEG 10–20 system [43] (see Fig. 4).

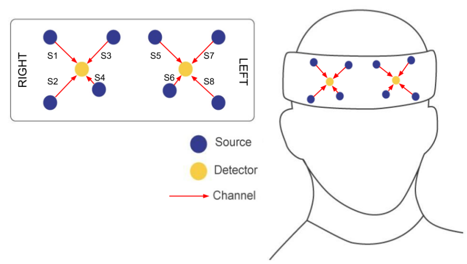


Fig. 4. Sensor Layout for *OctaMon*

3.4.6 *Data analysis.*

Behavioural Data. The search time of each of the three tasks and the number of bookmarked and viewed web pages were extracted by reviewing the screen recording. Then each participant's search performance and behaviour for each search task were represented by search time and BP/VP ratio.

Subjective MWL Measurement. Each participant's MWL for each of the three search tasks was analysed by averaging workload ratings during the task. Considering that the complexity level might vary for different participants depending on their familiarity with the search context, we additionally investigated the correlation between participants' ISA score and their familiarity with the search topics. This analysis aimed to determine whether task familiarity has an impact on workload to establish the results' reliability. Task familiarity was assessed using a Likert scale, where participants rated their familiarity with each of the three search topics from 1 (not at all familiar) to 5 (very familiar).

fNIRS Data. Signal processing was performed using the MNE-Python software [35]. The raw light intensity data measured with fNIRS was first converted into oxygenated (HbO) and deoxygenated (HbR) haemoglobin concentration changes using the Modified Beer-Lambert law [26] using a partial pathlength factor of 6.0 and the molar extinction coefficient table [115]. Temporal Derivative Distribution Repair (TDDR) [29] was applied to correct motion artifacts, and data was then bandpass filtered using an infinite impulse response Butterworth filter of order 4 with cutoff frequencies of 0.01 and 0.1 Hz. For each haemoglobin concentration change type (oxygenated and deoxygenated), the two short separation channels were averaged and regressed to the long-distance channels, resulting in 6 regressed long-distance

[1] https://www.artinis.com/octamon

channels each recording both HbO and HbR. We then extracted segments of interest ('epochs') for analysis using the start-of-search trigger (corresponding to the first input in the search bar) and using an epoch duration of 38 seconds, corresponding to the fastest search time across all the participants. Each epoch was baseline corrected using the one-minute baseline before participants started reading the instructions for each task as can be seen in Fig. 3. The analysis followed a block-averaging approach. The channels were averaged by region of interest to end up in 4 regions: left HbO, left HbR, right HbO, and right HbR. The features that were extracted from the epochs were: 1) the **area under the curve** over the whole epoch, 2) the **slope** of the linear regression on the 6 first seconds of each epoch, and 3) the **average** signal on the peak time range from 5 to 7 seconds from the search trigger onset (6 seconds approximately corresponding to the delay to reach cerebral blood flow's peak response [59]).

3.5 VICS Test

3.5.1 Test Description. We deployed Peterson et al. [82]'s VICS test using *PhychoPy*[2] [77]. PsychoPy can show the VICS test stimuli for accurate time periods, and record key responses, along with their corresponding timestamps into one Excel file for each participant. The images used were selected from the database developed by [99], which has been shown not to influence the participants' performance in the VICS test since they have no differences in *"name and image agreement, word frequency or age of acquisition"* [82]. For verbal-type tasks, 52 stimuli are man-made, 52 stimuli are natural, and 12 stimuli are mixed. The imagery-type tasks have 52 stimuli where the left item is larger than the right one, 52 stimuli where the left item is smaller than the right one, and 12 stimuli that are equal. All the stimuli in each section were displayed randomly.

3.5.2 Analysis and Creation of Groups. Participants' Verbal/Imagery (VI) ratio was calculated and used to classify participants into groups. After reviewing the experiment logs, one participant (Chinese speaker) was rejected since they did not follow the instructions of "please rest during the baseline recording between two of the search tasks", which prevented us from establishing a baseline. 29 participants' data were analysed for the remainder of the study.

[94] pointed out that the cutoff points for cognitive style grouping should consider the distribution of VI ratios in the sample but not absolutely a fixed range. Referring to [36] and [8], we used the median VI ratio of the sample (0.729697) as the cutoff point (the threshold value). Considering that one VI ratio corresponds to a specific position on the VI dimension [82] and represents the inclination to different cognitive style preferences, we inferred that there was a noticeable difference in cognitive style preference between the participants whose VI ratio was below (N=14) and above (N=14) the threshold value in the sample. Participants with VI ratio below the threshold value were classified as verbalisers and those with VI ratio above the threshold value were grouped as imagers. Since the number of participants was odd, the participant with the median VI ratio (English speaker) was also removed for further analysis.

4 RESULTS

An initial confounding variable check was conducted to determine whether language had an impact on the dependent variables. First, the balance of Chinese and English-speaking participants was equal for each cognitive style. Hence, differences in the language the participants used in our study did not affect the distribution of Cognitive Styles. We then examined each dependent variable for differences between the two language groups with a t-test if the normality of the distribution was verified (using a Shapiro test) or a Mann-Whitney U test otherwise. No significant differences between language groups were found for any of those variables (p-values greater than 0.05), namely task familiarity, search time,

[2] https://www.psychopy.org/

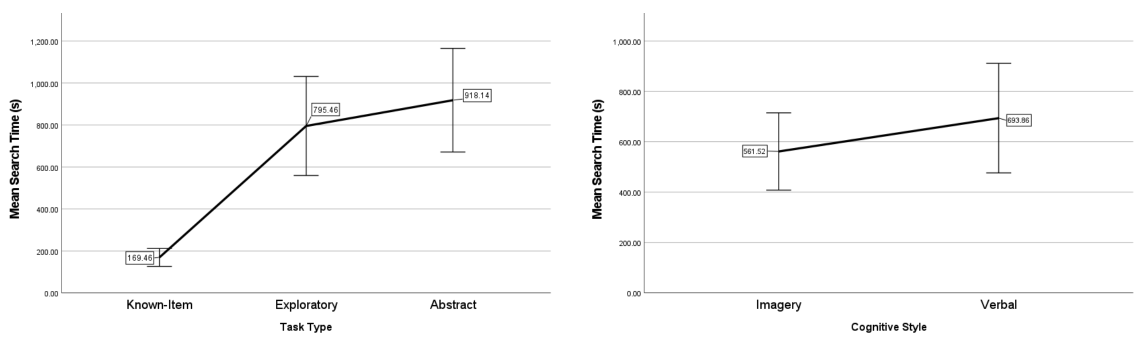
BP/VP ratio, ISA score, and fNIRS features (area under the curve, slope, average signal). Therefore, language was not considered in the subsequent statistical analysis of dependent variables.

4.1 Task Familiarity and Search Performance

We first studied the results of the "Task Familiarity" questionnaires, to know whether participants were overall more familiar with some tasks. A significant difference was found in task familiarity by a one-way ANOVA test ($F(2, 81) = 12.14, p < 0.001$) after confirming the data is normally distributed, with participants being most familiar with the *Abstract Searching* task, and least familiar with the *Known-Item Searching* task ($M_{Known-Item} = 1.89, M_{Exploratory} = 2.82, M_{Abstract} = 3.64$). The post hoc analysis with Bonferroni correction revealed the participants' familiarity level with the *Exploratory Searching* task ($p = 0.032$) and the *Abstract Searching* task ($p < 0.001$) was significantly higher than that of *Known-Item Searching* task, which should be considered when interpreting the results below. We therefore added task familiarity as an independent variable in our analysis.

Search performance was measured by search time. Since the data of the search time did not meet normal distribution, we adopted non-parametric techniques for the statistical analysis. As would be expected, a significant difference in search performance was found for different task complexities ($\chi^2(2) = 47.358, p < 0.001$), as revealed by a Kruskal-Wallis Test. After pairwise comparisons with Bonferroni correction, the analysis revealed that the search time for *Exploratory Searching* task ($p < 0.001$) and *Abstract Searching* task ($p < 0.001$) were significantly longer than *Known-Item Searching* task, but not significantly different to each other. The overall search time increased with the complexity of the search task ($M_{Known-Item} = 169.46, M_{Exploratory} = 795.46, M_{Abstract} = 918.14$) (see Fig. 5a).

A Mann-Whitney U Test examined the effect of cognitive style on search time. Although no significant difference was detected, the verbal participants' overall search time ($M = 694.85, N = 42$) was longer than the imagery participants ($M = 561.52, N = 42$) (see Fig. 5b). Similarly, a two-way ANOVA Test did not show a significant interactive effect of cognitive style and task complexity on search time.



(a) Mean search time under different search tasks

(b) Mean search time for different cognitive style groups

Fig. 5. Mean search time under different tasks and different cognitive styles, with 95% confidence intervals

4.2 Behavioural Data: BP/VP Ratio (H1 & H4)

Non-parametric techniques were applied for BP/VP ratio analysis as it was not normally distributed. A Mann-Whitney U Test examined the effect of cognitive style on the BP/VP ratio. The imagery group had a significantly higher BP/VP ratio than the verbal group ($M_{Imagery} = 0.097, M_{Verbal} = 0.089, U = 656.5, p = 0.044$) (see Fig. 6a), indicating that imagers visited fewer pages before making their bookmarks.

Again, as we would be expected by task design, the overall BP/VP ratio decreased as task complexity increased ($M_{Known-Item} = 0.144, M_{Exploratory} = 0.073, M_{Abstract} = 0.062$) , where participants viewed more pages in the two more open-ended tasks (see Fig. 6b). A significant effect of task complexity on the BP/VP ratio was revealed by a Kruskal-Wallis Test ($\chi^2(2) = 12.618, p = 0.002$), with the *Known-Item Searching* task requiring significantly fewer page views than the more open-ended tasks. The post-hoc analysis with Bonferroni correction showed a significant difference in BP/VP ratio between *Known-Item Searching* task and *Exploratory Searching* task ($p = 0.013$) and between *Known-Item Searching* task and *Abstract Searching* task ($p = 0.003$). Similarly, a Spearman rank-order correlation revealed a negative correlation between BP/VP ratio and search time, which was statistically significant ($r = -0.461, p < 0.001$), indicating a decreased BP/VP ratio (viewing more pages) as search time increased.

(a) Mean BP/VP ratio for different cognitive style groups

(b) Mean BP/VP ratio under different search tasks

Fig. 6. Mean BP/VP ratio under different tasks and different cognitive styles, with 95% confidence intervals

A two-way ANOVA Test explored the interactive effect of cognitive style and task complexity on the BP/VP ratio. The analysis did not show a significant result.

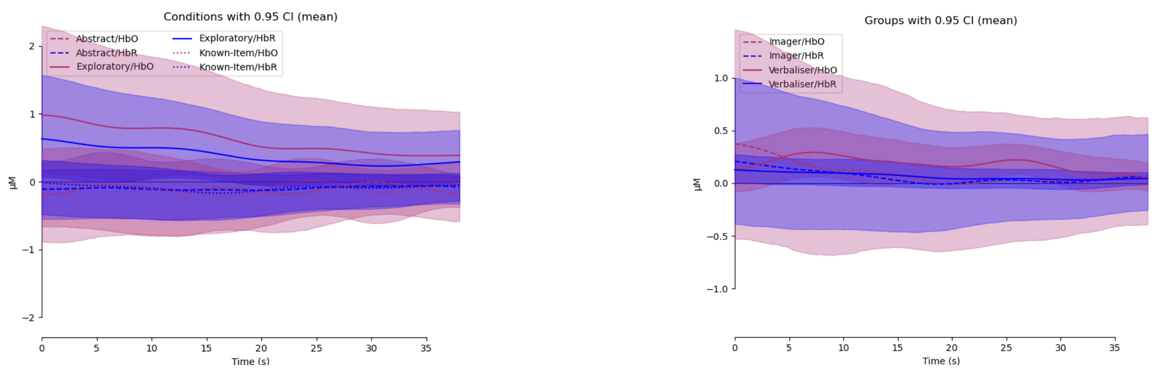
4.3 Subjective MWL Measurement (H2 & H5)

After confirming the data was normally distributed, a Pearson rank-order correlation determined that there was no relationship between task familiarity level and ISA score. Therefore, the statistic analysis related to subjective MWL only considered the ISA score. The overall ISA score in the verbal group ($M = 2.77$) was higher than the imagery group ($M = 2.74$), but a between-group T-Test did not reveal a significant effect of cognitive style on the ISA score. Perhaps interestingly, there was no significant effect of task complexity on the ISA score, the overall ISA score increased with the task complexity ($M_{Known-Item} = 2.54, M_{Exploratory} = 2.83, M_{Abstract} = 2.89$). Although the mean scores for *Exploratory Searching* task and *Abstract Searching* task are higher than *Known-Item Searching* task (as perhaps would be expected), the lack of statistical significance could have been moderated by the task familiarity (see above), or sample size.

A Spearman rank-order correlation, however, revealed a strong, positive correlation between ISA score and search time, which was statistically significant ($r = 0.693, p < 0.001$), indicating an increased MWL as search time increased. There was a significantly negative correlation between BP/VP ratio and ISA score ($r = -0.227, p < 0.01$), indicating a decreased ISA score as BP/VP ratio increased (fewer pages viewed).

4.4 fNIRS Data: Blood Oxygenation in the PFC (H3 & H6)

The three extracted features (area, slope, average) were analysed to determine whether they were significantly different depending on a) the search task complexity and b) the participants' cognitive style.



(a) Heaomoglobin concentration changes under different search tasks

(b) Heaomoglobin concentration changes for different cognitive style groups

Fig. 7. Heaomoglobin concentration changes averaged across all epochs and all channels per task complexity and cognitive style group for HbO and HbR. Bands represent the 95 % confidence interval related to the variability across epochs.

A two-way analysis of variance was performed on the data to study the influence of the condition, the group, and the interaction of those two variables on the different features for each region of interest. We observed a significant influence of the conditions (task complexity) on the HbR **slope** on left side ($F(2, 78) = 3.543, p < 0.05$). We also observed a significant influence of the group (cognitive style) on the HbO **slope** for both sides ($F(1, 78) = 6.057, p < 0.05$ for the left side and $F(1, 78) = 5.436, p < 0.05$ for the right side). No significance was found with the analysis of variance for the **areas** under the curve or the **average** signal on the peak time range. Pairwise t-tests with Bonferroni correction showed a significant difference in the **slope** in HbR on the left side ($t = 2.76, p = 0.015$), with the slope being higher for the *Abstract Searching* task (slope of 0.007) than the *Exploratory Searching* task (slope of -0.024) (see Fig. 7a).

Comparing epochs from the two different VI groups, a one-tailed independent t-test was used if the normality of the distribution was verified (using a Shapiro test) otherwise a Mann-Whitney U test was used. We observed a significant difference in the **slope** of HbO both on the left and right sides with the slope being higher for verbalisers than imagers (a Mann-Whitney U test for the left side with $U = 1165, p = 0.006$, and a t-test for the right side with $t = 2.34, p = 0.011$). On the left side the HbO slopes were 0.034 and -0.033 for verbalisers and imagers respectively, while they were 0.023 and -0.029 on the right side respectively (see Fig. 7b).

5 DISCUSSION

Overall, we were primarily concerned with examining the impact of cognitive style on searching behaviour and the MWL involved in searching. Our two-tailed hypotheses proposed that there would be a difference between verbalisers and imagers, especially when factoring in changing task complexity; e.g. we expected the MWL and search behavioural differences to be more evident in longer or more complex tasks. We discuss our findings below based on the RQs we proposed, followed by a discussion of implications and future work.

5.1 Main Findings

We observed that mean search time increased with task complexity (*Known-item Searching* < *Exploratory Searching* < *Abstract Searching*) and that the difference across all three search times as significant. More specifically, pairwise comparisons showed that participants took significantly longer to complete *Exploratory Searching* and *Abstract Searching* as opposed to *Known-item Searching*. The findings are consistent with prior work [33, 38].

RQ.a *Does cognitive style, on the VI dimension, have a noticeable effect on search behaviour?*

The overall BP/VP ratio of the open-ended tasks was significantly lower than that of the closed-end task, which means that participants viewed more pages that they did not bookmark for the *Exploratory Searching* and *Abstract Searching* tasks as opposed to *Known-item Searching*. This finding supports the prior finding about searching time. This can be explained by the correlation between information need generation and task complexity. In the three-step information search process model [107], searchers will generate their final information needs after several rounds of background information searching to understand and explore the search topic's context. The difficulty of forming well-defined information needs increased with the search task's complexity [109, 110]. The decreased BP/VP ratio supported our task design hypothesis.

While we did not see significant differences in search time (search performance) between our cognitive style groups, we did see that imagers visited significantly fewer pages, or rather, that verbalisers viewed more pages before bookmarking sufficient pages to complete the task. H1 is accepted based upon page visitations and bookmarking behaviours. Based on Kinley's analysis [51, 53, 54] of the relationship between viewed and bookmarked pages, our results suggest that verbalisers preferred a *Sporadic* navigation style and adopted a *Scanning* strategy as they processed information, whereas imagers preferred the *Structured* navigation style and reading information in detail.

Although tasks led to a significantly different number of page visits, the interaction between task complexity and cognitive style was not significant (H4 rejected). This suggests that the participants' search behaviour would not change under different task complexity but more associated with their cognitive style. It highlights the significance of considering cognitive style in future information retrieval studies.

RQ.b *Does mental workload during complex search differ by VI cognitive style?*

Subjective-rated MWL (ISA score) has shown a correlation with increasing task complexity and a significant increase with search length (time). We suspect that since participants were more familiar with the more complex tasks (as per our questionnaires), the increase in subjective workload was not as clear as expected, hence the non-significance of our result. Participants did not report significantly different levels of MWL between the cognitive style groups (H2 rejected), although perhaps interestingly, there was no significant difference in subjective ratings of MWL (ISA score) between the types of tasks either. This indicates that overall the MWL involved in these forms of searching did not create noticeable differences in perceived MWL for different cognitive style participants. Because MWL correlated with search length, and search length was significantly different for different tasks, we could recommend H5 be partially accepted. This could lead us to think that even if participants found the more complex tasks harder, this may have been compensated by the extra time they could take to complete them.

Conversely, though, in our more objective MWL recordings using fNIRS data, we found differences between *Abstract Searching* and *Exploratory Searching* tasks (H6 partially accepted, more evidence needed). More importantly, we saw a significantly increased slope in heamoglobin oxygenation for verbalisers in both halves of the prefrontal cortex (H3 accepted). This sharper brain activity increase would suggest a higher mental workload for verbalisers compared to imagers while performing those tasks. This significant difference is in the same direction as the trend that verbalisers viewed more pages that they did not bookmark and spent more time searching.

5.2 Implications and Future Work

Our result highlighted the importance of considering cognitive style in future search engine design for enhancing usability and avoiding inducing additional MWL. For instance, verbalisers preferred results that could help them reveal the final information needs quickly, while imagers wanted to explore each of the information needs they generated, which was in line with Kinley et al.'s findings [51, 54]. In this regard, a search prompt could be tailored based on the searcher's cognitive style to provide better support. The design of the search engine result pages (SERPs), including both rank orders of the result items and the layout of SERPs, is another aspect that our study can provide insights into. SERPs for verbalisers could be changed to show the keywords instead of a paragraph as "abstract" to summarise the contents in the corresponding hyperlink, as verbalisers scan the SERPs quickly before making any decisions. Our findings can also be used for adapting the navigation forms between web pages to users' cognitive style to enhance search engine usability.

While the key contribution of our study highlights the potential of tailoring the search engine based on the searchers' personality (such as cognitive style) as highlighted by [5], much more work is needed to understand a) how to identify such users, and b) how best to make these adaptions. While it is unlikely we will expect people to be classified by cognitive style before using search systems, larger scale and more complex analyses of search behaviour (e.g. [40]) could, for example, identify interaction patterns that match these groups and examine search success for them. Such larger log-based studies could also examine the impact of specific search user interface design changes on those search success metrics.

One limitation of our study, and a general challenge for future work that examines the search patterns relating to different cognitive styles, is in the classification of participants into groups. As with many studies that try to compare groups by cognitive traits [116], it can be challenging to actively recruit participants for each group. In our case, we classified participants according to their cognitive style score and split the pool down the middle to create two groups, and it is not clear, therefore whether more significant differences would be found if future research was able to recruit participants that were more clearly separate in each group. Recruiting such known groups is not a trivial task, and so future research projects may be able to recruit much larger samples of participants to identify more distinct subgroups whilst excluding participants with a mixed or central score on the scale. Larger future studies would also benefit from greater diversity in our participant sample, with more varied backgrounds, and more precise demographics could be collected in future studies to achieve this goal.

Our results did find some significant differences between verbalisers and imagers, but only in physiological response rather than as rated by the participants themselves. Given that the difference between tasks also did not lead to significantly different subjective experiences of MWL, it is interesting to consider whether the sensitivity of the physiological measure may be able to reflect something more fine-grained, in terms of actual experience, than subjective workload scales are sensitive to. Using physiological data could then enable to complement subjective measures and address some of their limitations. Furthermore, a more precise correlation of physiological measurements to specific events within each task could be studied to better understand search behaviour on a more specific and detailed level. Future work may find that considering cognitive style may only benefit different types of users at specific search stages [42, 69].

The significant differences, however, were subtle still in the physiological data. There could be several reasons for this, including task design. It may be that some other breakdown of task types may reveal or highlight the differences between these groups more evidently. Refinding tasks, for example, maybe more suited to imagery cognitive styles, where recognition of colour and layouts of web pages may be central to the task (e.g. [57, 92]). Conversely, it may be that tasks involving more critical interpretation of text may highlight the difficulty for imagery participants, where the difference between them could be identified by analyses of the amount of deeper levels of learning achieved [111]. Future work could further examine searching patterns in more detail, using more advanced measures of logged behaviour (e.g. [38, 52, 54]) and/or eye tracking (e.g. [55, 103]).

6 CONCLUSIONS

Our research aimed to compare the experiences of participants according to their cognitive style, particularly in the dimension between verbalisers and imagers, who process information better as words and as images, respectively. Although participants did not recognise much difference in complexity through their own subjective ratings, our use of functional Near Infrared Spectroscopy found significant differences in the oxygenation in the prefrontal cortex between groups, implying that verbalisers had higher levels of mental workload during the task. This difference was reflected in the non-significant trending data for time, but also in the significant difference in the number of pages viewed and bookmarked between groups. Our results indicate that verbalisers have a higher mental workload and engage with more pages when searching, especially in more exploratory forms of search. As for the meaning of having a higher mental workload, however, it is not yet evident if this is good or bad, where more mental workload could represent good engagement (having viewed more pages) or struggling to find information (therefore viewing more pages). Future work would need to look further at search outcomes and engage more qualitatively with participants to understand the meaning of such findings.

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Data Access Statement - Approval to share anonymised study data in a dataset was not gathered in the informed consent documentation during this international collaboration.

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