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The impact of personality traits on users' information-seeking behavior

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A B S T R A C T

Although personality traits may influence information-seeking behavior, little is known about this topic. This study explored the impact of the Big Five personality traits on human online information seeking. For this purpose, it examined changes in eye-movement behavior in a sample of 75 participants (36 male and 39 female; age: 22–39 years; experience conducting online searches: 5–12 years) across three types of information-seeking tasks – factual, exploratory, and interpretive. The International Personality Item Pool Representation of the NEO PI-R^{TM} (IPIP-NEO) was used to assess the participants' personality profile. Hierarchical cluster analysis was used to categorize participants based on their personality traits. A three cluster solution was found (cluster one consists of participants who scored high in conscientiousness; cluster two consists of participants who scored high in agreeableness; and cluster three consists of participants who scored high in extraversion). Results revealed that individuals high in conscientiousness performed fastest in most information-seeking tasks, followed by those high in agreeableness and extraversion. This study has important practical implications for intelligent human – computer interfaces, personalization, and related applications.

1. Introduction

Reliance on electronic materials for supporting information-seeking activities has increased and ability to process such information varies between individuals (Weiler, 2005). Several researchers emphasize the role of individual differences and cognitive factors in the information-seeking process. Marchionini and Shneiderman (1988) have addressed the importance of an understanding of the cognitive process in order to be used as the key link to one's information seeking. The process of information seeking is a cognitive activity that involves long-term and short-term memory, background knowledge, spatial cognition, and mental models, to name a few critical factors. Marchionini (1997) added that information seekers commonly relay on their mental models to guide them through different mental and physical activities that require predictable mental representations of the information objects and different domains of knowledge. Mental models are dynamic mental representations of the real world, and humans construct mental models of a phenomenon in order to understand it. Using this knowledge, Fidel and Pejtersen (2004) declared the role of individual complexity and variability to be the main driver of an actor, and every element in an actor's life experience, which may moderate one's information-seeking behavior. It was

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acknowledged that a number of individual characteristics can involve various combinations of perceptual, cognitive, and ergonomic attributes of the person doing the task.

Information-seeking behavior is important for providing a holistic view of information behavior (Heinström, 2005). As the relationship between personality and cognition has been studied as a means of predicting an individual's tendency to process information (Cantor & Kihlstorm, 1981), psychologists have focused on the relationship between personality traits and cognitive processing strategies. Dickman (1990) supports this claim, stating that personality traits drive the overall relationship between an individual and different information-processing tasks. Therefore, determining how different personality traits drive users' information-seeking behavior is important (Heinström, 2005, 2003, 2000). Personality traits are correlated with different mental states and actions or processes of acquiring knowledge and understanding through experience. Personality research has provided evidence about the relation between the way a person interacts with a task and that individual's genes and the environment (Kirzinger, Weber, & Johnson, 2012). In behavioral change research, different personality models have been proposed (Krikelas, 1983; Kuhlthau, 1991; Weiler, 2005) to explain individual differences in certain aspects of the self-socialization process.

Several researchers used eye-tracking to infer an individual's cognitive activities when attempting to retrieve information from the web. For example, Buscher, Cutrell, and Morris (2009) asserted that an understanding of how people allocate their visual attention when viewing Web pages is based on the fixation impact. They found that users' web-viewing behavior, as predicted by their eye-movements, is valuable not only for improving Web page design, but also for creating new types of Web user interfaces. Another study by Buscher et al. (2009) examined how visual attention devoted to organic results is influenced by these other page elements, such as ads and related searches. This provides an initial understanding of how individual elements combine to create a perception of the page as a whole. Wilson and White (2009) present a formative inspection framework for the evaluation of advanced search interfaces, through the quantification of interface strengths and weaknesses in supporting user tactics and varying user conditions. However, the retrieval of web page information has been linked to multiple dimensions in terms of time, place, history of interaction, task at hand, and a range of other factors that are not given explicitly, but are implicit in the interaction and ambient environment (i.e., the context) (Ingwersen & Järvelin, 2005). The use of contextual data can advance current practices used by a person when retrieving information through minimizing potential cognitive difficulties, which may persist during the retrieval process. Based on these studies, it is evident that most studies conducted in the past used eye-tracking in order to determine how people interact and process information while viewing results pages of search engines. These studies led to the characterization of typical gaze distributions on a page when attempting to perform various information retrieval activities. In addition, it was noted that most previous studies tend to use gaze data for understanding a person's attention and interaction with the different elements of a web page, which is aggregated across participants and tasks. The idea behind studying the effect of personality traits using eye movements was mainly to provide an interactive approach that enables users to organize information, structure their investigation of an information resource, or make interactive decisions. Buscher et al. (2009) suggested mapping gaze data to Web page elements, based on the concept of fixation impact, which refers to the surrounding area for each fixation that is used to determine the attention on the elements lie within this area. However, none of the previous studies attempt to explain the changes in people's gaze distribution with regard to personal characteristics, such as personality. This belief was established, based on the strong interaction between individual's personality structure coupled with information seeking tasks found by many studies (e.g., Heinström, 2005; Peter Willett, Heinström, Sormunen, & Kaunisto-Laine, 2014; Sin & Kim, 2013; Tidwell & Sias, 2005). Personality differences have been recognized as being influential to database searches, and are an important factor to consider in the design of information retrieval systems (Borgman, 1989). For instance, researchers like Heinström (2005) showed that personality traits and study approaches interact in their influence on general information-seeking patterns, while some information-seeking features could solely be explained by personality traits or approaches to studying. Peter Willett et al. (2014)) advanced this view further by stating how each of the traits had their own particular influence at various stages of the process. With these in mind, Ruthven (2008) highlighted the need for providing interactive support for searchers, by developing an interactive approach to enable users to organize information, structure their investigation of an information resource, or make interactive decisions.

According to Bachrach, Kosinski, Graepel, Kohli, and Stillwell (2012), personality traits might predict behavior in different information-processing activities. From the trait-congruency perspective, specific personality traits predispose individuals to seek out and process information in a manner congruent with those characteristics (Bargh, Chen, & Burrows, 1996; Neuberg & Newsom, 1993; Perlman et al., 2009).

From these observations, it appears that there is limited evidence of the impact of personality on information-seeking behavior, particularly eye movement. The present study attempts to fill this gap by examining eye-movement behavior in different information-seeking tasks. It uses Kim's (2008) categorization, where information-seeking tasks are divided into three types: factual, interpretative, and exploratory. The distributions of mean values of eye-movement parameters can differ by the nature of a task, "so randomly sampling from these distributions alone cannot distinguish the task that a person is engaged in" (Henderson, Shinkareva, Wang, Luke, & Olejarczyk, 2013). The findings may provide evidence on how to improve individuals' cognitive states while seeking information online.

2. Research questions

This exploratory study was conducted to answer the following research questions:

R1: Which eye-movement parameters are correlated with personality traits in online information-seeking behaviors? In particular, we were interested in the main effect of personality traits along with the interaction effects of these traits on information-seeking behavior.

R2: What is the main effect of personality traits on users' information seeking behavior? We were also concerned about whether user personality traits can predict performance in online information-seeking tasks.

R3: Can eye-movement parameters predict users' personality profiles in online information seeking?

The primary aims of this study were to provide an in-depth understanding of (a) the types of eye-movement parameters (e.g., fixation number, duration, amplitude, pupil diameter, and saccade duration) essential to explain users' seeking behavior on the Internet, (b) the effect of personality traits on these parameters across different information-seeking tasks, and (c) the feasibility of developing a model based on these parameters for predicting certain personality profiles online. This understanding can offer insight on how to enrich information-seeking experiences. The current results may be used to guide users to develop personality profiles sufficient for online seeking tasks.

3. Method

3.1. Ethical considerations

The ethics committee on human research at our university approved this study. The selected participants gave written informed consent.

3.2. Participants

This study used a convenience sampling method for selecting participants. The participants were 75 graduate students. The participants received a research credit in exchange for participation. Their ages ranged between 22 and 39 years. A preliminary check was conducted on the participants to ensure they had adequate experience in online searching and that they have normal or corrected-to-normal vision. They had similar experience of 5–8 years conducting online searches. The participants were screened to ensure they all had normal or corrected-to-normal vision. Those wearing eyeglasses were excluded from participation because eyeglasses pose difficulties in capturing eye movements.

3.3. Tasks

We used factual, interpretive, and exploratory information-seeking tasks. A factual task is defined as an information-seeking task where the user seeks a specific piece of data (e.g., the name of a place, product, a numerical value, or address). Factual tasks account for 25% of web search activity (Morrison, Pirolli, & Card, 2001). Compared to other tasks, factual tasks require less effort for users to interact with the systems (Li & Belkin, 2010). Interpretive tasks require users to actively create possible scenarios to interpret information with regard to its amount or quality (Kuhlthau, 1993). Exploratory tasks involve making use of facets in the search process beyond what can be observed from query refinements and click data, to formulate queries or navigate complex information spaces (Kules, Capra, Banta, & Sierra, 2009).

We used Kim's (2008) versions of factual, interpretive, and exploratory tasks. We made minor changes to the original tasks so that they would fit the context of this study; this included changing some terms to make them suitable for the participants' environment. Examples of the tasks are shown in Fig. 1. This study chose these three task types because they have different attributes in terms of task variables, such as information needed, task structure, types of information required, number of information components required, and content of information required. Since they differ in the described characteristics, they are assumed to lead to differences in information-seeking behavior.

Data collection for this study took place in a computer lab at the Centre for Instructional Technology & Multimedia, Universiti Sains Malaysia. The lab has the necessary equipment (laptop, eye-tracking device and software, and Internet connection) to ensure experimental validity; the required software and hardware were tested prior to the experiment. The default page in the Google Chrome browser was the Google search page.

Subjects were scheduled to perform the searches at their own pace. As each subject entered the lab, they were briefed about the study and asked to sign the consent form. A personality questionnaire was administrated to them before they began their search. The information seeking tasks, shown in Fig. 1, were assigned to each student, in a randomized order, to reduce the potential order effect. When subjects finished a given task, they were asked to click the link of the web page that contained the exact or relevant information. The guidelines and instructions given to the students, helped them to comprehend their tasks. While they were searching, each subject's screen activity was recorded in real time using an eye-tracking device, which captured their eye-movements in all the searching sessions.

A.
Factual Task:

You plan to visit Sarawak next week. One of your friends who has been there suggests that you visit the oldest seafood restaurant in town. You want to know the name of the restaurant.

B.
Interpretive Task:

Your cousin, a typical teenage girl, said that one of her friends had started to smoke. You fear your cousin might begin smoking in the near future and decide to educate her, so you have to find some information on what could happen if she starts smoking.

C.
Exploratory Task:

You have recently invested in CIMB Bank and you are interested in applying for loan to buy a house. You have heard that most loans in that bank follow certain conditions. You think you should learn about roles and regulations for meeting these conditions. The Web seems like a good place to locate this information.

Fig. 1. Information seeking tasks.

3.4. Personality measure

Goldberg's (1992) Five Factor Model of personality (also known as the Big Five) was employed. We selected this model because these traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness) have been empirically shown to be capable of describing personality. It was also used for the following additional reasons: first, because of its robust and parsimonious description of personality; second, because it has been used extensively in studies on different types of compulsive behaviors, which will allow a comparison of the results; third, it can be used to predict changes across time (Marlatt, Baer, Donovan, & Kivlahan, 1988; De Raad, 2000; Armon, Shirom, & Melamed, 2012). Participants completed a questionnaire assessing these traits.

The International Personality Item Pool Representation of the NEO PI-R^{TM} (IPIP-NEO), developed by Goldberg (1999), was used to assess the participants' personality profile. The questionnaire contains 300 items designed to measure the personality type across five dimensions. It is a self-report inventory of personality that assesses five broad domains and six lower-order facets of each domain. We administrated the questionnaire prior to the experiment in order to label the personality type of each participant who undertook the eye-tracking session. The labeling of the questionnaire was based on the participants' matrix number. Following informed consent, participants completed the online questionnaire. In the present study, Cronbach's alpha was over 0.6 for all subscales, indicating satisfactory reliability.

3.5. Apparatus

Eye movements were measured using an iView RED500 eye tracker (SensoMotoric), which recorded binocularly at 500 Hz. The iView X system tracks eye pupils by using infrared illumination, and processes and analyzes images of the eye in real time. Stimuli were presented using Experiment Center (SensoMotoric), on a 480 mm $\times$ 300 mm monitor (resolution = 1680 $\times$ 1050 pixels). Data were recorded with the iView X 2.5 software, following nine-point calibration plus validation with average accuracy of 0.45°. Fixations were detected with a saccadic-velocity-based algorithm (minimum velocity threshold = 40°/s, and minimum fixation duration = 50 ms). After data for all participants were calibrated, the system translated the pupil locations into gaze data, which we used to generate the prediction models.

3.6. Procedure

The participants were instructed to click a button to start the information-seeking tasks. During the calibration phase, we found that two participants failed to track the red dot on the screen due to some technical difficulties. Therefore, valid data from 73 participants were used in this study. A short practice trial was provided to accustom participants to the eye-tracking equipment and present the instructions. The three information tasks were arranged randomly; participants were asked to retrieve or obtain information for these tasks. Participants were asked to click on the link when they obtained the answer and then to move to the next task. All the trials of the information-seeking tasks were recorded. When they finished, participants closed the experiment page and were instructed to leave the eye-tracking room.

It was assumed that graduate students, with library experience and an information science background, would be more likely to be experienced searchers. In this way, the searcher's system knowledge factor could be controlled in this study.

Pre-processing of the data was carried out on the extracted data from the participants' eye-movements. The process took place at the initial stage of data cleaning and processing. Since we asked the participants to search the necessary information at their own pace, which varied from one participant to another, the data obtained here was from different pages, depending on the students' timing of the search result.

3.7. Data analysis

We stored the raw data of eye-movements with information about the time and position values for each web page, for every participant. Data screening and cleaning procedures were conducted using automated analysis software. Eye-movement parameters of fixation and saccadic were initially extracted independently from the positions of the target objects. In this study, saccades were considered when changes in eye position was greater than 8 pixels (about 8.8 min arc), in 15 ms or less. In addition, the duration the eye spent between two consecutive saccades was used as an indication of the fixation duration by the duration of each of those position samples (see Henderson, McClure, Pierce, & Schrock, 1997).

For the first research question (R1), Pearson's correlation analysis was used to assess the strength of the association between various eye parameters and personality traits. The following eye parameters were used in this study, because they are considered the most commonly used, and they depend on a number of stimulus properties and idiosyncratic factors, which are fixation number, fixation duration, average pupil size, saccade amplitude, and saccade duration (Pomplun, Reingold, & Shen, 2001; Hwang, Higgins, & Pomplun, 2007).

For the second research question (R2), a repeated-measures ANOVA was used to measure the main effect of the correlated personality traits on eye-movement parameters within groups. In case of a significant interaction, paired sample *t*-tests were used to assess the different effects of each personality trait on others and whether each personality trait and eye-movement parameter differed by between-subjects task groups. The IPIP-NEO was used in this study to determine how participants score on the Big Five personality dimensions. This test was acknowledged by Goldberg to be more precise in estimating the personality traits on 5 broad domains and 30 subdomains of personality as follows:

- Extraversion (Friendliness, Gregariousness, Assertiveness, Activity level, Excitement-seeking, Cheerfulness)
- Agreeableness (Trust, Morality, Altruism, Cooperation, Modesty, Sympathy)
- Conscientiousness (Self-efficacy, Orderliness, Dutifulness, Achievement-striving, Self-discipline, Cautiousness)
- Neuroticism (Anxiety, Anger, Depression, Self-consciousness, Immoderation, Vulnerability)
- Openness to experience (Imagination, Artistic interests, Emotionality, Adventurousness, Intellect, Liberalism)

IPIP-NEO measuring the mean and standard deviation (SD) for a sample of participants and interpret the submitted scores within one-half SD of the mean as the "average." Scores outside that range are interpreted as "low" or "high." If the scores are normally distributed, this would result in approximately 68% of persons being classified as average, about 16% as low, and 16% as high (see http://www.personal.psu.edu/~j5j/IPIP/ipipneo300.htm).

For the third research question (R3), we used a machine-learning tool (Weka) to classify the participants' eye-movement parameters extracted from the eye tracker. We used the lazy learning algorithm IB1 as a classifier, as most other classifiers must commit to a single hypothesis that covers the entire instance space. IB1 offers high efficiency in evaluating potential solutions. It helps establish classification predictions from predefined instances, where other algorithms do not typically maintain a set of abstractions derived from specific instances (Aha, Kibler, & Albert, 1991). In addition, classification with lazy learning uses a richer hypothesis space, which can increase the accuracy of classification. A leave-one-out cross-validation method was used to prevent bias while evaluating the performance of the classification models in a cross-validation fold. In this phase, the selected classifier was trained on all but one trial of data and then applied to the left-out test trial to identify its class membership, until each trial was classified. The accuracy of the classification was predicted based on the proportion of correctly classified instances from the training dataset. We also evaluated the performance of classification models based on a comparison to an empirically generated null distribution from non-informative permutations of labels in the training set, as recommended by Pereira, Mitchell, and Botvinick (2009).

4. Results

4.1. Correlation results

Correlations between personality traits and eye-movement parameters are shown in Table 1. In all three tasks, conscientiousness, extraversion, and agreeableness were correlated with fixation number, fixation duration, and average pupil size. Openness and neuroticism were not significantly correlated with fixation and saccadic parameters, while agreeableness and extraversion were significantly correlated with fixation duration in only one task.

Table 1
Correlation results for personality traits and eye movement parameters in factual, exploratory, and interpretive tasks.

	Fixation number	Fixation duration	Saccade amplitude	Saccade duration	Average pupil
Factual task					
Openness	.011	.013	.114	.004	.107
Conscientiousness	.233**	.312**	.102	.032	.210**
Extraversion	.273**	.298**	.163**	.186**	.364**
Agreeableness	.332**	.340**	.041	.100	.251**
Neuroticism	.109	.085	.112	.021	.011
Exploratory task					
Openness	.071	.110	.016	.032	.050
Conscientiousness	.190**	.211**	.002	.012	.231**
Extraversion	.212**	.311**	.012	.018	.214**
Agreeableness	.332**	.340**	.118	.100	.210**
Neuroticism	.109	.085	.001	.053	.080
Interpretive task					
Openness	.084	.115	.100	.118	.107
Conscientiousness	.217**	.274**	.083	.042	.199**
Extraversion	.283**	.222**	.119	.007	.221**
Agreeableness	.195**	.218**	.233**	.221**	.190**
Neuroticism	.153	.002	.107	.016	.103

** Correlation is significant at the 0.01 level (2-tailed).

Table 2.
Descriptive statistics of eye-movement parameters for participants high in conscientiousness, agreeableness, and extraversion across three information-seeking tasks.

	Fixation number Mean & SD	Fixation duration Mean & SD	Pupil size Mean & SD
Factual task			
Group 1	77.60 (SD = 15.81)	474.27 (SD = 34.52)	12.21 (SD = .73)
Group 2	35.29 (SD = 11.00)	412.74 (SD = 26.00)	10.90 (SD = .97)
Group 3	37.92 (SD = 12.32)	352.33 (SD = 52.46)	11.03 (SD = 1.16)
Exploratory task			
Group 1	81.04 (SD = 5.01)	401.11 (SD = 24.54)	11.31 (SD = .04)
Group 2	102.23 (SD = 2.11)	455.02 (SD = 21.10)	12.41 (SD = .25)
Group 3	93.21 (SD = 13.31)	420.71 (SD = 34.20)	13.21 (SD = .89)
Interpretive task			
Group 1	96.36 (SD = 23.04)	420.10 (SD = 19.00)	12.01 (SD = .35)
Group 2	60.44 (SD = 10.24)	398.21 (SD = 26.00)	11.56 (SD = .32)
Group 3	40.00 (SD = 9.21)	382.01 (SD = 22.74)	10.98 (SD = 1.11)

Group 1 (high in conscientiousness)
Group 2 (high in agreeableness)
Group 3 (high in extraversion)

4.2. Repeated-measures ANOVA

A repeated-measures ANOVA was used to measure the effect size of personality traits on these parameters in the three tasks. We first performed hierarchical cluster analysis to detect and group patterns based on participants' personality traits. The cluster analysis result yielded a three-cluster solution. The first cluster consisted of 28 (38.35%) participants who scored high in conscientiousness, the second group consisted of 24 (32.87%) participants who scored high in agreeableness, and the third group consisted of 21 (28.77%) participants who scored high in extraversion.

Table 2 shows the descriptive statistics of eye-movement parameters among the three groups (Group 1: conscientiousness, Group 2: agreeableness, and Group 3: extraversion) with regard to the three seeking tasks. There was a significant main effect of fixation number in the three tasks, $F(2, 852) = 231.43$, $p < 0.001$. The mean number of fixations significantly differed across tasks, $F(2, 852) = 231.41$, $p < 0.001$. T-tests showed that subjects fixated the most in the factual task, followed by the exploratory and interpretive tasks. It appears that participants were showing a high level of concentration in the factual task as compared to exploratory and interpretive tasks. Therefore, we measured the interaction between number of fixations in the three tasks and participants' personality traits. Personality traits showed a significant effect, $F(2, 72) = 27.20$, $p < 0.001$. The interaction between fixation number and personality traits with regard to the three seeking tasks was significant, $F(4, 848) = 169.79$, $p < 0.001$. This interaction shows that the number of fixations in the information-seeking task differed significantly among participants with high conscientiousness, agreeableness, and extraversion.

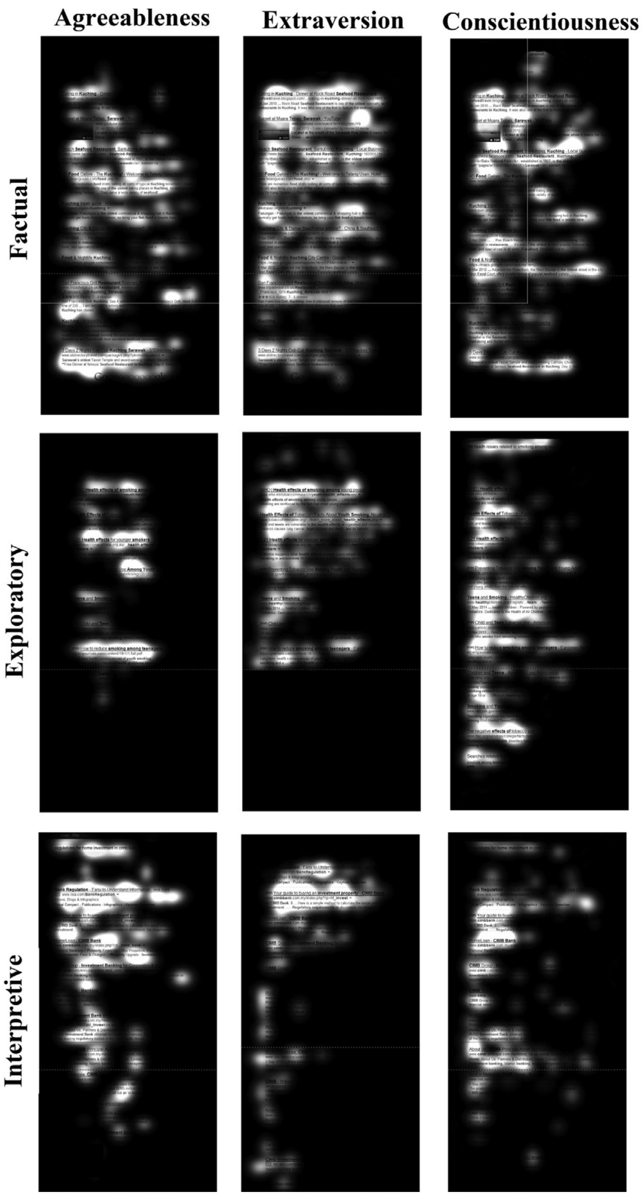

Fig. 2 . Focus map for the information-seeking behaviors based on participants' personality traits.

There was a significant main effect of fixation duration in the three seeking tasks, $F(2, 848) = 10.96$, $p < 0.001$. The mean fixation duration differed significantly across tasks, $F(2, 852) = 18.50$, $p < 0.001$. T-tests showed that subjects fixated significantly longer during the factual task than the exploratory and interpretive tasks. Thus, participants generally concentrated the most in the factual task, followed by exploratory and interpretive tasks. The interaction between fixation duration and personality traits with regard to the three seeking tasks was significant, $F(2, 424) = 3.96$, $p = 0.020$.

There was a significant main effect of average pupil size in the three seeking tasks, $F(2, 848) = 1.79$, $p < 0.001$. Pupil size significantly differed across tasks, $F(2, 852) = 33.66$, $p < 0.001$. Participants showed significantly higher concentration on the factual task than the exploratory and interpretive tasks. Pupil size was also higher for the exploratory than the interpretive tasks. Participants showed highest concentration in the factual task, followed by exploratory and interpretive tasks. The interaction between pupil size and personality traits with regard to the three seeking tasks was significant, $F(4, 848) = 25.84$, $p < 0.001$.

We also visualized the scan path of participants in the three tasks with regard to their personality traits (Fig. 2). Conscientiousness was related with visual processing in the factual task, leading to rapid improvement in participants' seeking speed. However, there was no such relationship for exploratory and interpretive tasks.

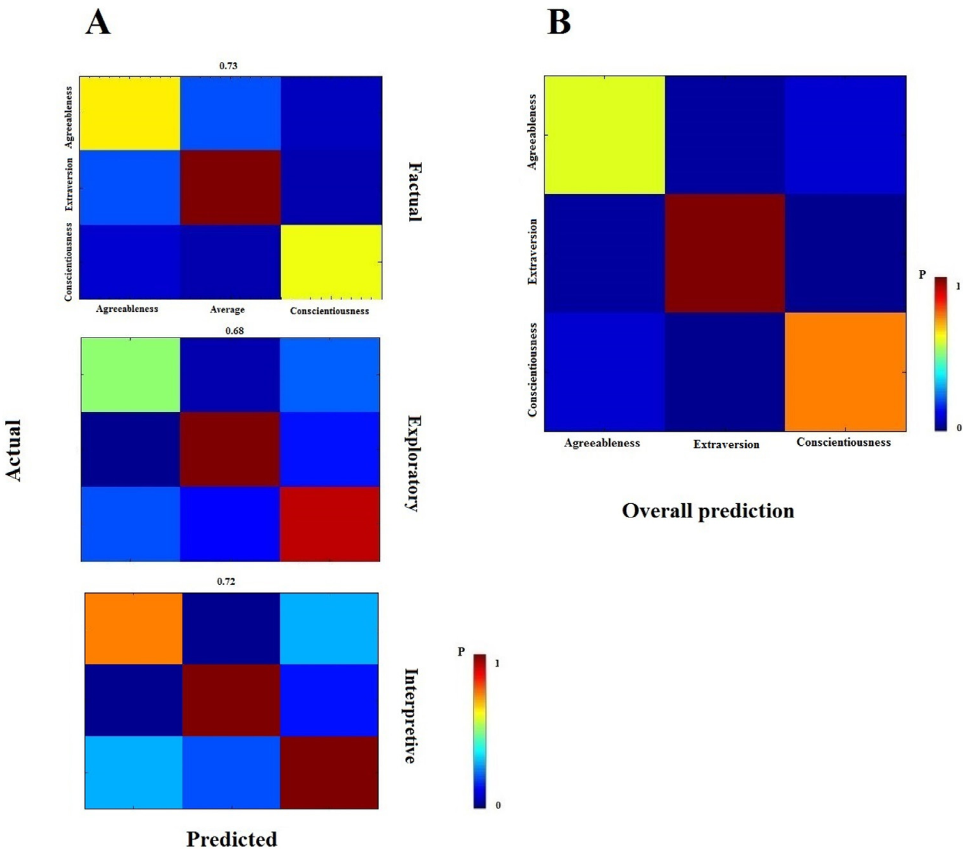

Fig. 3 . Confusion matrices of prediction accuracy.

Participants with relatively high extraversion had a relatively small pupil size while seeking information. In contrast, participants high in conscientiousness exhibited fewer fixations and shorter fixation durations to extract information in most of the three tasks. Participants high in agreeableness exhibited longer fixation durations for extracting information in all tasks. Those with high conscientiousness performed better than did those with high extraversion and agreeableness. Moreover, participants high in agreeableness and conscientiousness exhibited similar eye movement behavior in the exploratory and interpretive tasks.

4.3. Prediction results

In order to consolidate these findings, we used the IB1 learning algorithm to build the prediction model based on inputs from the eye-movement parameters (fixation number, fixation duration, and average pupil size) correlated with personality traits (conscientiousness, agreeableness, and extraversion). A confusion matrix was used to present the actual and predicted classifications from IB1. Precision was used to address the proportion of the predicted instances that were correctly classified. The results of the factual, exploratory, and interpretive tasks show that eye-movement parameters can explain the personality traits of conscientiousness, agreeableness, and extraversion (Fig. 3A). Further, model performance for these tasks was strongly correlated with the personality traits of extraversion, conscientiousness, and agreeableness, respectively. Different personality traits can be accurately predicted from individuals' eye-movement behavior in various information-seeking tasks (Fig. 3B).

Panel A: Confusion matrices for the three types of information seeking for all participants ordered by task type and with classification accuracies placed above each matrix. The row and column of each matrix indicate the proportion of personality traits in the three information-seeking trials that are the "actual category." A perfect classification result in a confusion matrix with 1s on the diagonal and 0s as the off-diagonal elements. Panel B: Represents the overall prediction accuracy across the three types of information seeking. Precision (P) is the proportion of positive predicted cases.

We also visualized the distribution of the instances among fixation number, fixation duration, and average pupil size to gain an in-depth understanding of the probability distribution of these parameters based on the density level between instances for each personality trait. By examining the probability distribution of the instances for each class (Fig. 4), we can conclude that every personality trait forms its own distribution, which can be used to visualize the effect of different

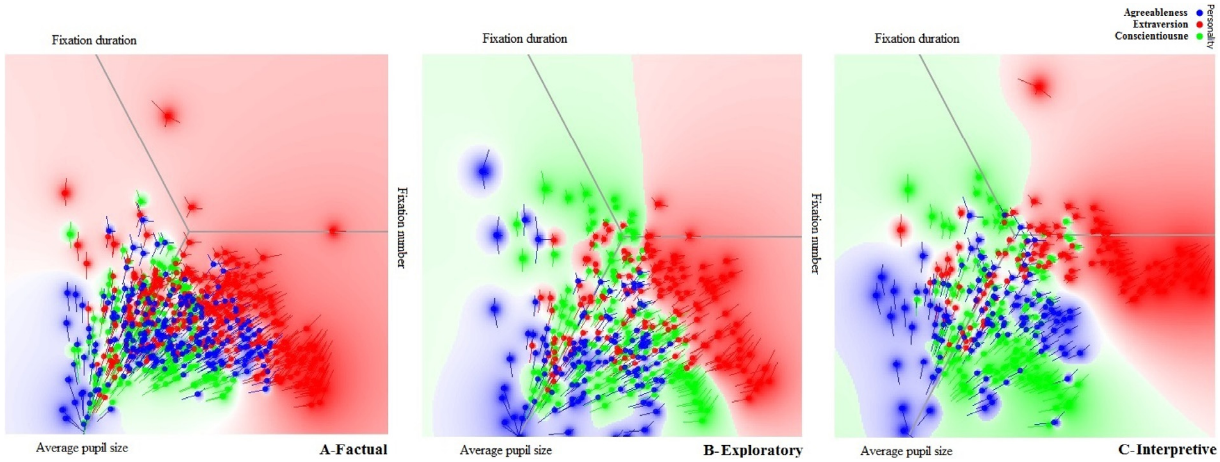

Fig. 4 . Density distribution for predictors over personality traits.

personality traits. It is also worth mentioning that the distribution of personality traits for the three information-seeking task types may vary across tasks. This can be explained by the nature of the task, as factual tasks need more analytical searching strategies than do other information-seeking tasks.

5. Discussion

Many vision perception studies have examined the relationship between personality and patterns of eye movements in scene-viewing contexts (Kaspar & König, 2011; Kelly, Miellet, & Caldara, 2010). Others have examined how different Big Five traits are related to vision perception in visual processing tasks (e.g., Matsumoto, Shibata, Seiji, Mori, & Shioe, 2010; Perlman et al., 2009). Extending the contributions of these studies, we found that certain eye parameters (fixation number, fixation duration, and pupil size) in online information-seeking tasks can indicate a person's personality profile. These parameters have the potential to be used in explaining users' seeking behavior.

Our results lend support to Kelly et al. (2010) claim that the time spent on a visual processing task is indicative of personality differences. Further, they accord with Risko, Anderson, Lanthier, and Kingstone (2012) finding that perceptual curiosity associated with certain types of personalities can be predicted by the extent to which individuals explore different scenes. We also found a significant difference in participants' eye-movement behavior across the three seeking tasks. Based on the interaction effect, we found that correlations between personality traits and eye movement parameters differed by task. These findings complement those of Rauthmann, Seubert, Sachse, and Furtner (2012), who reported that high agreeableness and conscientiousness can affect eye movements. They also enrich Dickman's (1990) findings, which showed that personality traits drive the overall formation of processing tasks.

The factual information task represents a common process performed by Internet users, and it demands that the user seek a specific piece of data (Morrison et al., 2001). Individuals high in conscientiousness seem to scan and decide on information faster than individuals high in other traits do. This can be explained by the fact that participants high in conscientiousness engage in some kind of mental reflection (Mortimer, 1995). This explains why conscientiousness had the greatest impact on information seeking in factual tasks, followed by agreeableness and extraversion.

The differences in the eye-parameters in the exploratory task can be explained by the nature of such tasks, which results in different information-seeking modes (Kim, 2007). That is, individuals high in agreeableness processed with fewer fixations and longer durations to retrieve information, while individuals high in extraversion required shorter durations to do so. Thus, extraversion has the strongest effect on the speed of performing online exploratory tasks, followed by agreeableness and consciousness.

In the interpretive task, participants high in conscientiousness and those high in extraversion exhibited similar tendencies in their use of information-seeking strategies, such as scan-info-recognize, a strategy previously reported in research using interpretive tasks (Kim, 2007).

We also found that eye movements can be used to predict individuals' information-seeking behavior based on their personality profile. Such predictions were highly accurate for the people high in extraversion, followed by conscientiousness and agreeableness. Individuals high in extraversion and conscientiousness process information with stable fixations in almost all types of information-seeking tasks. Kim (2008) found differences in users' information-seeking behavior in tasks as compared to other types of tasks. His proposed reason for this finding was that factual tasks require more analytical searching strategies than do other information-seeking task types. This claim relates to our finding that participants' eye movement behavior in the factual task was distributed in a heavily contextual manner compared to the exploratory and interpretive tasks.

One practical implication of our finding is that they can inform the development of computers and smartphones with user-facing (front) cameras that customize/adjust viewers' visual information-seeking tasks based on the personality profile mapped from their eye movements. The display can also be altered in a context-sensitive manner based on eye-movement inputs. However, although the Big Five model covers a broad range of personality traits, the Big Five alone (without considering cognitive or perceptual behavior) cannot be used to adjust displays, because trait descriptors do not perfectly fit into simple structure models (Hofstee, De Raad, & Goldberg, 1992). Our findings are also theoretically important because they contribute to the research on factors predicting personality traits in cognitive processing tasks and cross-classification contexts. There has been an increasing demand for data to clarify the effect of personality on cognitive states.

6. Conclusion

This study revealed a relationship between eye-movement parameters and personality traits, which affect information-seeking behavior on the Internet. Our results show that the number of fixations, fixation duration, and average pupil size have the potential to explain and predict a person's personality profile in online information seeking. On the basis of these findings, it is possible to develop novel methods of enhancing users' information-seeking experiences, in which displays are adjusted on the basis of users' personality traits, determined by their gazing behavior. This study also introduces the possibility of using probability distributions to characterize the eye-movement behaviors for each personality profile, which can enable artificial intelligence systems to customize users' information-seeking settings.

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