Using Eye Gaze Data and Visual Activities to Infer Human Cognitive Styles: Method and Feasibility Studies

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ABSTRACT

Recent research provides evidence that individual differences in human cognitive styles affect user performance and experience in diverse application domains. However, state-of-the-art elicitation methods of cognitive styles require researchers to apply explicit, in-lab, and time-consuming "paper-and-pencil" techniques, rendering real-time integration of cognitive styles' elicitation impractical in interactive system design. Aiming to elaborate an implicit elicitation method of cognitive styles, this paper reports two feasibility studies based on an eye-tracking multifactorial model. In both studies, participants performed visual activities of varying characteristics, and the eye-tracking analysis revealed quantitative differences on visual behavior among individuals with different cognitive styles. Based on these differences, a series of classification experiments were conducted, and the results revealed that gaze-based implicit elicitation of cognitive styles in real-time is feasible, which could be used by interactive systems to adapt to the users' cognitive needs and preferences, to better assist them, and improve their performance and experience.

CCS CONCEPTS

• **Human-centered computing** → HCI theory, concepts and models • **Computing methodologies** → Machine learning approaches

KEYWORDS

Human Cognitive Styles; Eye-Tracking; Visual Search Tasks; Visual Decision-Making Tasks; User Study.

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1 INTRODUCTION

People develop different strategies when they seek, process, retrieve, and reconstruct information, as they are characterized by different cognitive attributes (*e.g.*, skills, abilities, styles) [1]. Recent research provides empirical evidence that individual differences, in such cognitive attributes, affect task performance and user experience across diverse application domains, such as e-learning [2], information visualization [3], security [4], e-shopping [5], web search [6], and video-gaming [7].

To understand and explain empirically the observed differences in mental representation and information processing, a number of researchers [8–11] have focused on high-level cognitive processes, known as *cognitive styles*. Cognitive styles refer to the preferred way an individual processes information, and they describe a person's typical mode of thinking, remembering, or problem solving [12]. The integration of cognitive styles as a human design factor would be beneficial for interactive system users, as they would experience real-time services and functionalities, tailored to their individual needs and preferences, through adaptation and personalization frameworks.

However, the barrier in such research endeavors is the explicit and non-real-time elicitation of the human cognitive styles. Nowadays, their elicitation is based on traditional in-lab (*e.g.*, "paper-and-pencil" [11, 13]) and time-consuming (*e.g.*, 15-20 mins [11, 13]) techniques, rendering real-time integration of cognitive styles' elicitation impractical in interactive system design.

To overcome this issue, implicit elicitation mechanisms could be used. These mechanisms provide information regarding user characteristics through intelligent and automatic modelling processes, while the user is interacting with the system. Such information is extracted transparently, without interrupting the users, while performing activities. Given that there is a strong correlation among human cognitive styles, activity, and visual behavior [14], and as visual scanning and processing are principal stages of performing visual activities, eye gaze data could reveal measurable differences and allow for inferring cognitive styles. Hence, eye-tracking mechanisms could be used to implicitly elicit cognitive styles in real-time, based on quantitative differences on visual behavior within certain types of visual activities.

The motivation underlying our work is moving toward an implicit and real-time elicitation framework of human cognitive styles, based on an *eye-tracking multifactorial model* of: *human cognition, visual behavior*, and *activity* factors (Fig. 1). Such a model could provide appropriate data for any interactive system to know, and adapt to the users' cognitive needs and preferences, to better assist them (*e.g.*, improve task performance and user experience), so they can benefit from adaptation interventions. Such a framework should rely both on ground-truth data derived from state-of-the-art, credible, and validated tools used traditionally for cognitive styles' elicitation, and on quantitatively measured differences on visual behavior within certain types of activities, evidenced on validated and credible studies.

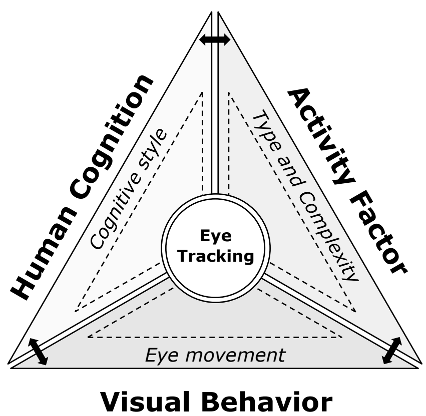

Figure 1: Eye-tracking multifactorial model for implicit elicitation of cognitive styles. It consists of three main factors: human cognition, visual behavior, and activity.

Aiming to create an eye-tracking multifactorial model to identify human cognitive styles implicitly and in real-time, and provide the classification results as a service to any information system, to dynamically adapt to its users' characteristics, the contribution of this paper is two-fold: i) analyze eye gaze data, aiming to reveal gaze behavior and patterns that are indicative of people with different cognitive styles, and ii) infer cognitive styles using such eye gaze data, while performing certain types of activities. Thus, this paper details the method used to model users' visual behavior, and reports two feasibility studies to justify the use of the eye-tracking multifactorial model to elicit human cognitive styles implicitly and in real time, using varying parameters of visual activity and eye gaze measures.

The reminder of the paper is structured as follows. First, we provide an overview of related research in implicit elicitation of human cognitive styles. Next, we present the interplay among the factors of the eye-tracking multifactorial model. This is followed by two studies that we performed to examine the feasibility of the proposed implicit elicitation process. We conclude the paper with a discussion on the main findings, limitations, and future steps.

2 RELATED WORK

Several studies [15–17] suggest an interplay effect among human cognitive styles and user visual behavior while performing certain types of activities. To the authors' knowledge, none of them has elaborated on an implicit and real-time elicitation framework of human cognitive styles based on eye gaze data, taking into consideration varying activity factors (*e.g.*, type, complexity).

Barrios et al. [18] developed AdELE, an adaptive framework of e-learning resources, which detects users' cognitive styles based on the holistic/analytic and verbal/imagery dimension [8] through eye-tracking. However, no sufficient evaluation regarding the user classification was provided. Moreover, AdELE does not consider the type and the characteristics of the activity (*e.g.*, difficulty, sequence), which influence the visual behavior [19, 20].

Nisiforou and Laghos [17] showed that individuals with different cognitive style, have different visual approaches in terms of low-level eye-tracking metrics (*e.g.*, number of fixations) when performing visual search tasks. However, the visual strategy (*e.g.*, scan-paths) the users followed was discussed only qualitatively, and despite the insights gained, such non-quantitative differences could not be used to elicit cognitive styles implicitly in in-real time scenarios. Moreover, they did not investigate other types of activity and varying activity factors (*e.g.*, complexity, sequence).

A number of studies have reported alternative methods to infer human cognitive styles, which are majorly limited to navigation schemes. Belk et al. [21] proposed a set of navigation metrics to reveal the holistic or analytic cognitive style of individuals, when performing a Web navigation task. Chen and Liu [22] proposed a method to identify users' cognitive styles by tracking their behavior with navigation tools. Wang et al., [23] proposed a method to identify cognitive styles from user-generated social media content. Chan et al. [24] tracked how users with different cognitive styles use mobile Web search tools in e-journals.

While the aforementioned research endeavors contribute towards the implicit elicitation of human cognitive styles, they are limited to the application domain (*e.g.*, e-learning, e-commerce). In addition, these approaches are unable to leverage principal stages of information processing (*e.g.*, visual scanning and visual processing) to accurately infer human cognitive styles in activities where interactions with means other than eye gaze are limited.

In contrast to high-level cognitive processes, a number of studies have reported on using eye gaze data to identify low-level cognitive attributes (*e.g.*, skills and abilities). Steichen et al. [20, 25] classified individuals according to their perceptual speed, verbal and visual working memory attributes when performing information visualization tasks; Yelizarov and Gamayunov [26] developed a mechanism to detect its users' cognitive overload and adapt the amount of displayed information accordingly.

Therefore, we argue that eye-tracking mechanisms could be used to implicitly classify the individuals based on their high level cognitive processes (*i.e.*, cognitive styles) in real-time while performing activities of varying characteristics (*e.g.*, type complexity). Nowadays, this is realistic, as the recent technological advances have enabled the development of affordable, robust and mainstream eye-tracking solutions.

3 MULTIFACTORIAL MODEL FOR IMPLICIT ELICITATION OF COGNITIVE FACTORS

In order to explore a visual scene, humans perform varying visual activities which incorporate information processing to some extent, depending on the nature of the visual activity, and thus they involve human cognition. These are the three main factors (*i.e.*, human cognition, activity, and visual behavior) which form the eye-tracking multifactorial model (Fig. 1) that we propose to infer human cognitive styles, and their interplay has a major impact on individuals' task performance and user experience [14]. The reminder of this section is concerned with the eye-tracking multifactorial model for the implicit elicitation of cognitive styles (*i.e.*, factors, eye-tracking, and implicit elicitation method).

3.1 Human Cognition Factor

The *human cognition* factor reflects on theories of individual differences in information processing, suggesting that individuals have preferred ways of seeking, representing, processing and retrieving information, depending on their individual cognitive skills and abilities, (*e.g.*, perceptual speed and memory load) [10, 27, 28]. Several researchers have focused on high-level cognitive processes to explain empirically such observed differences [1]. These processes are called *cognitive styles*, and a number of them have been developed and studied over the years [8, 10, 11, 28].

The human cognition factor of our multifactorial model is based on a fundamental and credible [29, 30] cognitive style theory: the *Field Dependence-Independence (FD-I)* [10]. FD-I classifies people as field-dependent (FD) or field-independent (FI). FDs tend to prefer a more holistic way when processing visual information, and have difficulties in identifying details in complex scenes [10]. On the other hand, FIs tend to prefer a more analytical information processing approach, pay attention to details, and easily separate simple structures from the surrounding visual context [10].

Several studies have provided empirical evidence that the differences among FD and FI individuals reflect on their task performance and user experience. Mewed et al. [5] have shown that FI consumers developed a more analytical information processing strategy on decision-making e-shopping tasks (*e.g.*, selecting a yogurt product). Raptis et al. [7] evidenced that FI gamers performed better, in terms of game assets collection, when playing a cultural heritage adventure game. Shinar et al. [31] evidenced that FD drivers were less adaptive and efficient in changing environments (*e.g.*, curve negotiating), where the perceptual load was drastically increased and the target area (*i.e.*, the road) changed iteratively within their visual field.

3.2 Visual Behavior Factor

The *visual behavior* factor reflects on visual perception (*i.e.*, the ability to identify, organize and interpret the surrounding environment by processing visually displayed information). Visual perceptual span varies in visual tasks, depending on diverse task sub-characteristics (*e.g.*, difficulty, sequence, and hierarchy level), and it is interrelated with eye movements [32]. The basic eye movements are saccades, fixations, smooth pursuits, compensatory eye movements, vergence, and optokinetic nystagmus [33].

Research has revealed that individuals with different cognitive style, differ in visual behavior. Shi et al. [34] showed that FD drivers produced less and slower fixations when driving; Zhuomin and Wanyi [35] revealed that FI users fixated on web advertisements for longer time periods during Web navigation; Wijnen and Groot [36] used scan-paths produced by participants' fixations to show that FI individuals develop a more analytical and systematic strategy to find hidden figures within complex ones; Huang and Byrne [37] used lateral eye movements (*i.e.*, left and right eye shifts) to evidence that holistic individuals tended to produce more left shifts when viewing an image, while analytic individuals tended to produce a majority of right shifts; Puig et al. [38] showed that FIs had stronger eye convergence than FDs; and that the angle of eye vergence was larger for the FIs compared to the vergence angle of the FDs on visual attention tasks. Hence, we argue that in our multifactorial model, the most suitable visual behavior factor depends on the visual activity characteristics.

3.3 Activity Factor

Activity characteristics, such as type (*e.g.*, visual exploration, visual search, pattern recognition) influence visual behavior of individuals with different cognitive styles [14]. Visual activities can be broken into smaller components (*i.e.*, visual tasks), which, according to Gidlöf et al. [39], can be broadly classified as *visual search tasks* and *visual decision-making tasks*. During visual search tasks, individuals look for specific information in a given information complex (*e.g.*, pattern recognition), while on visual decision-making tasks, individuals make choices among alternatives (*e.g.*, graphical password creation).

Raptis et al. [40] revealed that FI gamers developed more and longer fixations while visually searching for in-game assets when playing an adventure game. Mawad et al. [5] showed that FDs produced less and shorter fixations on visual decision-making tasks (*e.g.*, select a dairy product to buy). Nisiforou et al. [17] showed that FDs produced more saccades and fixations while searching for differences in shapes. Crosby and Peterson [41] evidenced that individuals with different cognitive styles differ in the way they visually search for information on sorted and unsorted lists, as they follow different visual scanning strategies (*i.e.*, different scan-paths).

Apart from type, tasks differ in other characteristics, such as difficulty, complexity, sequence, and hierarchy level, which affect the performance and the experience of individuals with different cognitive styles [3, 32]. Conklin et al. [42] showed that FDs had longer and more random eye movements during visual search tasks, as the complexity of the background scene increased. Nisiforou et al. [19] showed that the visual search strategies of FD and FI individuals were complexity-dependent on Web navigation. For webpages of low complexity the visual search strategies of FD and FI individuals were similar. However, the scan-paths of FD individuals appeared to be more disoriented and scattered on webpages of medium and high complexity, in contrast to FI individuals, who displayed more oriented and organized scan-paths.

3.4 Eye-tracking Layer

The aforementioned studies suggest that there are inter-dependencies among human cognition, visual behavior, and activity factors, which affect individuals' performance and user experience. To leverage on the interplay among these factors, eye gaze data are used. The eye-movement data is captured through eye-tracking tools, which serve as the connection layer among the factors, helping us understand the visual behavior and the strategy of individuals with different cognitive styles when performing activities of varying characteristics.

A number of eye-tracking data and measures of diverse complexity have been developed, such as fixations and saccades, fixation duration [33], trending scan-path analysis [43], and gaze transition and stationary entropies [44]. The selection of the most suitable eye-tracking metrics depends on the activity characteristics. To perform a credible eye-tracking analysis, specific areas of interest (AOIs) (*i.e.*, clustered sub-regions of the displayed stimulus in which the eye-tracking metrics are applied) must be defined appropriately [25].

Depending on the three factors of the multifactorial model, specific eye-tracking metrics and AOIs are defined, to proceed on the user modelling process and elicit human cognitive styles implicitly and in real-time.

3.5 Implicit Elicitation

The user modeling process for eliciting users' cognitive styles entails three main phases: *data collection*, *data processing,* and *classification.*

Data Collection

Collecting data of users is the initial step for implicit elicitation of cognitive styles. In our multifactorial model, the data refers to raw eye gaze data, which is captured through the eye-tracking layer. The raw eye gaze data varies, depending on the eye-tracking technology (*e.g.*, sampling frequency) used. The gaze data is assigned to each user profile, and provided to the next phase for data processing.

Data Processing

The data processing phase is two-fold: i) to decide which eye-tracking measure is the most suitable to perform the classification, and ii) to transform the data to the corresponding measure. The selection of the most suitable measures depends on the activity and the cognitive style characteristics. The transformation of the data entails both the form of the eye-tracking metrics set (*e.g.*, fixation duration, gaze entropies), and the definition of the AOIs in the displayed stimuli.

Classification

The final phase to elicit cognitive styles is the classification process. When the transformed eye-tracking measures are provided in our model, the corresponding individuals are classified based on their cognitive style. The classification is based on a valid data set, provided by credible studies, which is used to train our model to make predictions. Along with the classification process, the prediction certainty is estimated for each individual.

4 FEASIBILITY STUDIES

In order to examine the feasibility of the proposed implicit elicitation process, we conducted two studies, with individuals performing different types of visual activity based on Gidlöf et al. [39] (*i.e.*, a visual search and a visual decision-making activity), with FD-I being the independent cognitive style variable.

Both studies consist of two phases: *classification metrics extraction* and *classification experiment.* Phase A consists of an eye-tracking study aiming to reveal whether there are statistically significant differences in individuals' visual behavior while performing activities of specific type, and identify which these are. These differences reflect on specific eye-tracking measures and AOIs, which are intended to be used as classification parameters to train the learning model used for the classification experiment in Phase B. To perform the classification experiment in Phase B, we conducted a second eye-tracking study, following the same experimental design as in Phase A. Its purpose was to collect the gaze data from a new set of users (testing set), to evaluate the classification model. We used the WEKA [45] data mining toolkit for model learning and evaluation. The training and testing sets used (for both feasibility studies) were balanced.

In both studies, the participants' eye movements were recorded with Tobii Pro Glasses 2 wearable system, while performing each activity. Following common practice, we focused on where and when fixations occurred. Fixations were extracted using a customized velocity threshold identification (I-VT) algorithm [46], based on the I-VT algorithm provided by Tobii.

4.1 Study I – Visual Search Activity

The first feasibility study entails a visual search activity. FD-I measures the ability of individuals to identify simple details in complex visual scenes, and thus, it reflects on visual search, and specifically on pattern recognition [10]. The pattern recognition activity was based on a traditional "paper-and-pencil" FD-I elicitation tool: *Group Embedded Figures Test (GEFT)* [13, 47], as it is a ground-truth tool for FD-I classification. GEFT consists of 25 pattern recognition tasks of varying complexity (*i.e.*, very easy, easy, medium, difficult and very difficult [9, 48], based on the visual complexity of the pattern). For each task, the participants are asked to identify and outline a simple figure within a complex one. The test consists of two main sections, with each section lasting 5 minutes and consisting of 9 pattern recognition tasks. The number of simple figures correctly identified constitute the score (ranging from 0 to 18), which is used to classify the subject as FD or FI (*i.e.*, the higher the score, the more FI the subject is).

Phase A: Classification Metrics Extraction

Hypothesis. The following null hypothesis was formed: ***$H0_1$***: there is no significant difference between FDs and FIs in terms of visual behavior throughout visual pattern recognition tasks of varying difficulty.

Study procedure. We recruited 67 participants (29 females), ranging in age between 20 and 47 (31.1 ± 6.4), who had to meet a set of minimum requirements (*i.e.*, have never taken the GEFT before, and have no vision problems). Each participant undertook GEFT, and their score ranged from 1 to 18 (11.4 ± 3.7).

Study analysis. The analysis of the gaze data focuses on the comparison of participants' visual search strategy in relation to their cognitive style and the difficulty level of each pattern recognition task. We focused on the visual search behavior of the extreme types of FDs and FIs, as personalization has significant impact on such users. According to the participants' GEFT scores, we had 9 extreme FDs (*i.e.*, individuals who scored lower than 6) and 12 extreme FIs (*i.e.*, individuals who scored higher than 15).

According to the FD-I theory, we expected that FDs and FIs would follow a different visual search strategy. FIs were expected to follow a more oriented and organized approach, while FDs a more disoriented one. An eye-tracking metric that quantifies such behavior is the *gaze transition entropy* proposed by Krejtz et al. [44]. In general, entropy measures the lack of order or predictability (*i.e.*, the higher the entropy, the more disordered a system is). Accordingly, the gaze transitions made through specific AOIs of a stimulus, and the stationary distribution of eye-movements over the stimulus, have an impact on visual search behavior. They are expressed through transition entropy H_t, and stationary entropy H_s. Lower values of H_t indicate more careful viewing of AOIs, while greater H_t values indicate more randomness and more frequent switching between AOIs. Lower values of H_s are obtained when fixations tend to be concentrated on certain AOIs, while greater H_s indicates that visual attention is distributed more equally among AOIs. Each complex form of the pattern recognition task was divided into three vertical AOIs (Fig. 2), as originally performed in Krejtz et al. [44].

For each entropy type, we performed a within-subjects 2x5 ANOVA, with cognitive style (FD and FI) and task difficulty (very easy; easy; medium; difficult and very difficult) as the independent variables, and H_t and H_s as the dependent variables. In both cases, the 2x5 ANOVA tests met all assumptions.

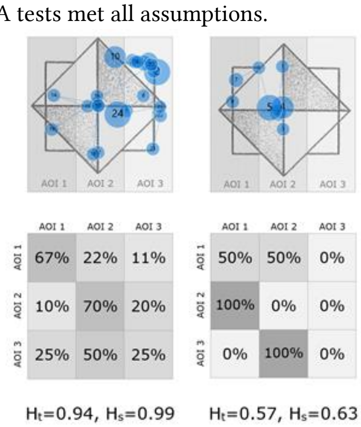

Figure 2: The scan-paths are transformed in transition matrixes, displaying the probability to perform a gaze transition across three vertical AOIs. The matrixes are then transformed in transition H_t and stationary H_s entropies.

Gaze transitions among AOIs. The results indicated that there was a statistically significant interaction effect between cognitive style and visual search task difficulty for transition entropy H_t (F=6.212, p<.01, *partial* η^2=.430). On very easy, easy and moderate tasks FIs had similar H_t values with FDs. However, as the complexity of the background figures increased, the H_t values differed significantly, with FIs having lower levels of H_t than FDs in both cases (*t=2.141, df=18.014, p=.046* for difficult tasks, and *t=2.221, df=18.815, p=.038* for very difficult tasks). The higher H_t values of FDs indicate more randomness regarding their eye movements and a more exploratory character of their visual attention, rather than a systematic approach (Fig. 3).

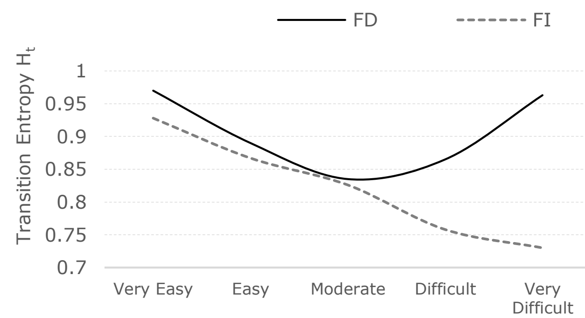

Figure 3: FI individuals produced more gaze transitions among AOIs (expressed in transition entropy H_t) than FDs. Their difference increases, as the task complexity increases

Distribution of visual attention on AOIs. The results indicated that there was a statistically significant interaction effect between cognitive style and visual search task difficulty for stationary entropy H_s (F=3.406, p=.019, *partial* η^2=.292). On very easy, easy and moderate tasks FIs had similar H_s values with FDs. However, as the complexity of the background figures increased, the H_s values differed significantly, with FIs having lower levels of H_s than FDs in both cases (*t=2.217, df=14.705, p=.043* for difficult tasks, and *t=2.189, df=18.928, p=.041* for very difficult tasks). Higher H_s values mean that subjects distribute their visual attention more equally among AOIs; lower ones show that their fixations are concentrated on certain AOIs (Fig. 4).

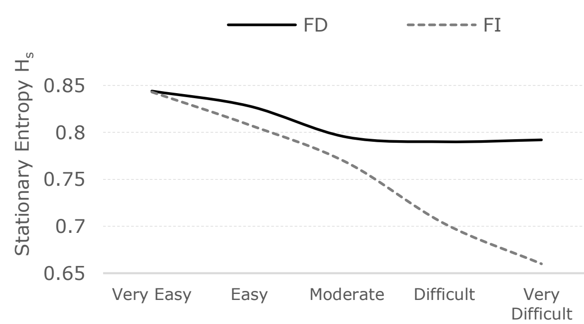

Figure 4: FD individuals distributed their attention more equally among AOIs (expressed in stationary entropy Hs) than FIs; the difference increases as the task complexity

Both findings indicate that individuals who have different cognitive styles, have also quantitatively different visual search approaches (in terms of transition and stationary entropies), when performing pattern recognition tasks of varying complexity. Their differences in visual search strategy are strongly correlated with the complexity factor of each task, which is highly correlated with participants' completion time and total score of GEFT [49].

Phase B: Classification Experiment

Training phase. The first step of the classification process is to build and test the training model. We formed the model training set, based on the extracted classification metrics of Phase A (*i.e.*, transition and stationary entropies). For model learning, we tried a number of different classifier types (Logistic Regression, Naïve Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines), with feature selection and 5-fold cross-validation for model evaluation (as we had a small dataset). Naïve Bayes (NB) performed best in terms of accuracy and, precision and recall (*i.e.*, F measure). NB classifier had accuracy of 80% (statistically significant difference from the other classifiers tested) and F measure of 72%. As a baseline of comparison, we used a classifier that always selects the most likely class (ZeroR).

The training model was based on the gaze entropies for both difficult and very difficult tasks, and thus the users should perform both tasks to collect the appropriate data. It is worth examining the training and testing performance of models based on each difficulty level. For the difficult task, k-Nearest Neighbor (kNN) classifier performed best (accuracy: 72%, and F measure: 71%); and for the very difficult task, NB classifier performed best (accuracy: 75%, and F measure: 72%).

Testing phase. To validate our classification scheme, we conducted a second eye-tracking study to collect gaze data and form the testing set. We recruited 21 individuals (9 females), aged between 25 and 41 (30.5 ± 4.2), who had to meet a set of minimum requirements (*i.e.*, had never taken GEFT before, and have no vision problems). All participants undertook GEFT, and their scores ranged between 4 and 18 (11.1 ± 3.9). Ten individuals were classified as FD, and eleven were classified as FI. Participants' eye-movements were recorded, and then analyzed in transition and stationary gaze entropies, forming the classification metric vector.

The task of the classifier is to infer whether a user belongs on either the FD or FI category for a given measure. Based on gaze entropies (both transition and stationary) and on difficulty levels (difficult and very difficult), NB classified correctly 81% of users (9/10 FDs and 8/11 FIs were correctly identified). The prediction certainty of NB classifier was 82.22% ± 16.67% for FDs, and 79.86% ± 19.88% for FIs. A notable point is that the false predictions were made on relatively low certainty rates (60.4% for the misclassified FD, and 50.6%, 61.3%, and 65.4% for the misclassified FIs).

As discussed, it is worth investigating whether we can achieve high accuracy scores, based only on one task difficulty level, to decrease the number of tasks required by the user to perform, and consequently the time needed, to infer the cognitive style. Based on gaze entropies for the difficult task only, kNN classified correctly the 67% of users (7/10 FDs and 7/11 FIs). Based on gaze entropies for the very difficult task, NB classified correctly the 76% of users (9/10 FDs and 7/11 FIs).

The NB classifier had high accuracy score (81%) when based on both task types (higher than the baseline classifier: 53%, as our sample was balanced). High accuracy was also achieved using only the very difficult task (76%), meaning that the cognitive style could be inferred measuring the gaze entropies only for one type of difficulty, and thus perform the classification in less time, which is vital in real-time applications.

4.2 Study II – Visual Decision-Making Activity

The second feasibility study entails a visual decision-making activity. Graphical user authentication (GUA) is a representative visual decision-making activity, as the users create their graphical passwords by visually scanning, processing, and deciding on the available options. For our study, a recognition-based GUA scheme was designed and developed, following guidelines of well-cited GUA schemes [50, 51]. The GUA scheme (Fig. 5) consisted of a grid of 120 unique images, and the users had to select five images in a specific order, to create their graphical password. Each image could only be selected once in a single password. The provided image policy was based on existing approaches and is typical in recognition-based GUAs [52, 53]. The graphical authentication activity consists of five sequential tasks (*i.e.*, selection of the first, second, third, fourth and fifth images).

Figure 5: The GUA scheme consisted of 120 images (AOIs). Users had to select five images to create their passwords.

Phase A: Classification Metrics Extraction

Hypothesis. The following null hypothesis was formed: $H0_2$: there is no significant difference between FDs and FIs in terms of visual behavior throughout visual decision making tasks of specific sequence.

Study procedure. We recruited 51 individuals (16 females), aged between 18 and 40 (29.3 ± 5.8), who had to meet a set of minimum requirements (*i.e.*, have never taken GEFT before, have no vision problems, and have no experience with recognition-based GUA schemes). Each participant undertook the GEFT to be classified as FD or FI. Next, the participants used the designed GUA scheme to create a graphical key.

Study analysis. The analysis of the gaze data focuses on the comparison of participants' visual decision-making strategy in relation to their cognitive style and the sequence of each image selection task. Like in the visual search study, we focused on the extreme FDs and FIs. According to their GEFT scores (ranged between 4 and 17; 9.9 ± 3.1), we had 9 FDs and 11 FIs.

Several studies [7, 29, 54] indicate that FIs need more time to complete a visual decision-making task, as they tend to follow a more analytical approach. Such behavior reflects on low-level eye-tracking metrics, such as *fixation duration* and *number of fixations*. Hence, for each metric, we performed a within-subjects 2x5 ANOVA, with cognitive style (FD and FI) and task sequence (1st image selection; 2nd image selection; 3rd image selection; 4th image selection; 5th image selection) as the independent variables; and fixation duration and fixation count as the dependent variables. The AOIs of the study were the 120 grid images. In both cases, the 2x5 ANOVA tests met all assumptions.

Fixation duration per image selection. The results indicated that there is a statistically significant interaction effect between cognitive style and task sequence level on fixation duration (F=4.386, p=.003, *partial* η^2=.171). The fixation duration of FIs (54.30 ± 32.12 sec) was significantly longer than FDs' (19.78 ± 18.80 sec), from GUA load until the selection of the first image (F=29.664, p<.001, *partial* η^2=.259). No significant differences of fixation duration were revealed between FIs and FDs on selecting the second, third, fourth, and fifth image (Fig. 6).

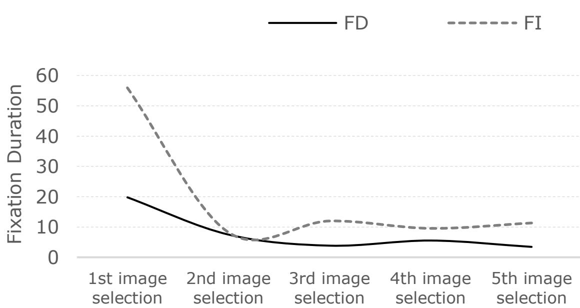

Figure 6: FIs had longer fixations than FDs, from the GUA load until the selection of the first image.

Fixation count per image selection. The results indicated that there is a statistically significant interaction effect between cognitive style and task sequence level on fixation count (F=4.172, p=.004, *partial* η^2=.156). The fixations made on the AOIs by FIs (76.01 ± 51.11) were significantly more than the ones made by FDs (24.89 ± 20.09), from GUA load until the selection of the first image (F=25.952, p<.001, *partial* η^2=.224). No significant differences of fixation count were observed between FIs and FDs on selecting the second, third, fourth, and fifth image (Fig. 7).

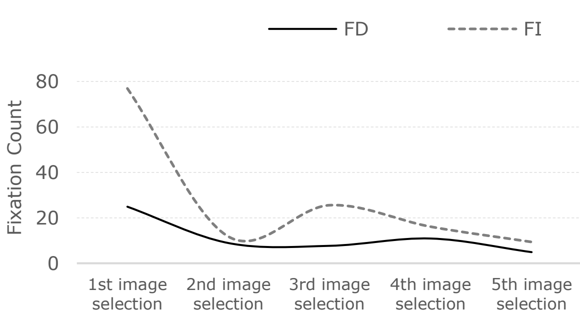

Figure 7: FIs produced more fixations than FDs, from the GUA load until the selection of the first image.

Both analyses show that FIs have significantly more and longer fixations than FDs for the selection of the first image. The difference of the two groups lies in the analytical nature of FIs, which in this case, is reflected on the larger number of images they visually scanned before deciding the first image, compared to the holistic nature of FDs, which is reflected on a more random selection of images, and thus a quicker first image selection.

Phase B: Classification Experiment

Training phase. The first step of the classification process is to build and test the training model. We formed the model training set, based on the extracted classification metrics of Phase A (*i.e.*, number and duration of fixations until the first image selection). For model learning, we tried a number of different classifier types (Logistic Regression, Naïve Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines), with feature selection and 5-fold cross-validation for model evaluation (as we had a small dataset). Naïve Bayes (NB) and Logistic Regression (LR) performed best in terms of accuracy and, precision and recall (*i.e.*, F measure). NB classifier had accuracy of 76.5% and F measure of 76%, while LR classifier had accuracy of 76.0% and F measure of 74%. As a baseline of comparison, we used a classifier that always selects the most likely class (ZeroR classifier).

Testing phase. To validate our classification scheme, we conducted a second eye-tracking study to collect gaze data and form the testing set. We recruited 20 individuals (9 females), aged between 25 and 38 (29.7 ± 4.1), who had to meet a set of minimum requirements (*i.e.*, have never taken GEFT before, have no vision problems, and have no experience with recognition-based GUA schemes). Each participant undertook the GEFT, to be classified as FD or FI, Their scores ranged from 3 to 18 (9.1 ± 3.4), and then, they used our GUA scheme to create a graphical key. Ten individuals were classified as FD and ten were classified as FI. Participants' eye-movements were recorded, and then analyzed in number and duration of fixations from page load until the first image selection. The fixation count and duration values for each individual form the classification metric vector, which then was used for the classification process.

The task of the classifier is to infer if a user belongs on either the FD or FI category for that measure. NB classified correctly 90% of users. All FDs were correctly identified, while 8/10 of FIs were correctly identified. The prediction certainty for FDs was 92.61% ± 1.96%, and for FIs it was 92.49% ± 8.49%. The false predictions had lower rates (75% and 81%). LR classified correctly 95% of users. All FDs were correctly identified, while 9/10 of FIs were correctly identified. The prediction certainty for FDs was 72.57% ± 6.38, and for FIs it was 80.59 ± 16.88. The false prediction had the lowest rate (56%).

Both classifiers (NB and LR) had high levels of accuracy, based on the extracted eye-tracking metrics, much higher than the baseline classifier (50%, as our sample was balanced). This level of accuracy was achieved by only using the data for the 1/5 (20%) of the total tasks required to create a graphical key. For this scope the elicitation is performed in less than one minute, and this could be an input to future adaptation and personalization schemes.

5 DISCUSSION

We proposed a method to infer human cognitive styles based on an eye-tracking multifactorial model. It consists of three main factors (human cognition, visual behavior, and activity), with an eye-tracking mechanism serving as the connection layer among them. The captured eye-tracking data is then used to classify individuals based on their cognitive style through an implicit elicitation process of three phases (data collection, data processing, and classification). As outlined in the introduction, the contribution of this work is two-fold: i) to investigate whether individuals of different cognitive styles have quantitatively measured differences in visual behavior and patterns (*e.g.*, number of fixations, gaze entropies, scan-paths) and ii) to infer cognitive styles using specific gaze measures, while performing activities of varying characteristics (*e.g.*, type, complexity, sequence),

To investigate the aforementioned questions, we conducted two feasibility studies, in which, individuals who were characterized as field-dependent or field-independent performed two visual activities of different type (*i.e.*, visual search and visual decision-making) and different characteristics (*i.e.*, complexity and sequence). Their eye movements were captured, processed, and transformed into specific eye-tracking measures, which were used to identify differences in the visual strategy the participants followed when performing each activity.

The eye-tracking analysis revealed that field-independent individuals followed a more organized and oriented visual search strategy when performing visual search tasks of increased difficulty, while field-dependent individuals followed a more disoriented approach. Their differences were quantitatively measured on transition and stationary gaze entropies. Based on these eye-tracking measures, we formed a training learning model on Naïve Bayes classifier (as it performed best). To test our model, we used the gaze entropy measures of a new dataset, and 81% of users were correctly identified, when considering both difficulty types; 67% when considering only the difficult tasks; and 76% when considering only the very difficult tasks.

When performing visual decision-making activities, field-independent individuals produced more and longer fixations on the first of the tasks required (sequence dependent activity). Based on both eye-tracking measures we formed a training learning model on Naïve Bayes and Logistic Regression classifiers (as they performed best). To test our model we used the fixation count and duration measures of a new dataset, and both classifiers performed well (90% accuracy rate for Naïve Bayes, and 95% accuracy rate for Logistic Regression).

In both cases, the classification scheme identified individuals correctly, based on their cognitive style, with high accuracy, and with low prediction certainty rates for misclassified individuals. Both classifiers were based on a small amount of collected eye gaze data to infer cognitive styles, and thus, the classification was completed in short-time. For example, in the visual decision-making sequence-dependent activity (Study I), the classification was based on only one of the five sequential tasks (20% of total tasks). Hence, the findings indicate that real-time elicitation is feasible.

In view of designing interactive systems that can adapt to individuals' preferred ways to visually process information, these findings provide important indicators as to which particular eye-tracking measures could be monitored for predicting and adapting to the various cognitive styles. Moreover, the findings indicate that such an implicit elicitation is feasible, and the model proposed can be used as a service for providing the classification results to information systems which support eye-gaze tracking, so the users can benefit from adaptation interventions.

Given that the recent technological advances have a major impact on the eye-tracking industry, the development and integration of affordable, robust, and mainstream eye-tracking solutions are expected to be widely applied to modern environments (*e.g.*, mixed reality) and assistive technology frameworks. In such frameworks, the eye movements play an important role, and thus, implicit elicitation through integrated eye-tracking tools, is realistic. Such an implicit elicitation mechanism could be complemented with varying eye gaze features, other interaction features, performance features, etc.

Regarding the generalizability of our method, the proposed model consists of dynamic and expandable layers (human cognition, visual behavior, activity), which form a knowledge base. The knowledge base is updated continuously with new validated data from credible studies, aiming to build more accurate learning models to improve implicit elicitation performance. In both studies the areas of interest were selected to be applicable to any corresponding visual activity type, thus contributing in the generalizability of our method. In particular, for the visual search activity, the overall task region was divided into three horizontal areas of same size, following Krejtz et al. [44] original approach. For the visual decision-making task, the areas of interest were the grid images.

The next step of this research is to conduct more feasibility studies, considering other cognitive styles, activity characteristics, and application domains, and increasing sample size, aiming to enhance the accuracy of the classification process, surpassing the limitations of the present studies. We envisage to develop an integrated implicit elicitation mechanism of cognitive styles to inform adaptive decisions in real-time based on eye-gaze data.

6 CONCLUSION

This paper revealed that individual differences in cognitive styles are quantitatively reflected on eye gaze data (gaze entropies, fixation duration and count) while users perform visual activities of varying type (*e.g.*, visual search, visual decision-making) and varying characteristics (*e.g.*, complexity, sequence). Moreover, this paper reported two classification experiments, which revealed that gaze data could drive the elaboration of an implicit elicitation process of human cognitive styles, with high accuracy level. Real-time and implicit elicitation of cognitive styles would open unprecedented opportunities for improving user experience and task performance through adaptation and personalization on a plethora of application and research domains, where literature has evidenced that individual differences, such as field dependence-independence, have a significant impact.

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