Eye Gaze-driven Prediction of Cognitive Differences during Graphical Password Composition

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ABSTRACT
Evidence suggests that individual cognitive differences affect users' memorability, visual behavior, and graphical passwords' security. Such knowledge denotes the added value of personalizing graphical password schemes towards the unique cognitive characteristics of the users. However, real-time and accurate cognition-based predictive user models are necessary to reach such a break-through. In this paper, we present the results of such an attempt, where an in-lab eye-tracking study was conducted with 36 participants who completed a recall-based graphical password composition task. We adopted a credible cognitive style theory, and investigated a variety of eye-tracking metrics to predict participants' cognitive styles. Results' analysis reveals that inferring individual cognitive differences in real-time during graphical password composition is feasible within a few seconds and that specific eye-tracking metrics correlate stronger with certain cognitive style groups. The findings further support the vision of incorporating real-time adaptive mechanisms in graphical password schemes for the benefit of service providers and end-users.

Author Keywords
Graphical User Authentication; Eye-Tracking; Human Cognitive Differences; User Modeling; Classification.

ACM Classification Keywords
• Human-centered computing ~ Human computer interaction (HCI) • Security and privacy ~ Human and societal aspects of security and privacy

INTRODUCTION
Graphical user authentication (GUA) is a widely deployed alternative to traditional text-based authentication. There are two types of GUA schemes: *recall-based* (i.e., users draw a graphical password) and *recognition-based* (i.e., users select a set of images to form a password). Despite that GUA was proposed as a possible solution for the memorability and security issues associated with textual passwords [19], recent research revealed that people make predictable choices in GUA too, affecting both the memorability and the security of passwords [2,6,12,14].

Predictable password choices are affected, among others, by cognitive characteristics [2,6,12], and when they are related to visual behavior, such as the Field Dependence-Independence (FD-I) theory [36], they affect password composition [14,15] and login [3] in GUA. FD-I suggests that individuals have different approaches in retrieving, recalling, processing, and storing visual information, and characterizes individuals either as *field dependent (FD)* or *field independent (FI)*, based on their ability to process visual information and identify details in complex scenes.

Despite that research results raise the need for providing assistive and/or adaptive mechanisms in the GUA domain, this is currently impractical since elicitation of FD-I style is achieved through time-consuming in-lab tools. Hence, this work aims to investigate whether user's FD-I style can be predicted implicitly in real-time during graphical password composition, using eye-tracking data, given that FD-I is related to visual behavior [18,21,24]. We envisage that this will enable GUA scheme designers to predict the users' cognitive characteristics, include a time-related predictive model to the GUA schemes, and provide design solutions catered for the users' cognitive characteristics during registration and/or login. This is of major importance considering that the users' cognitive characteristics have been associated with performance differences in terms of memorability and security, and such knowledge could be used to provide GUA schemes adjusted to users who share common cognitive characteristics to assist them during GUA tasks.

RELATED WORK
Several research attempts have been made to infer cognitive styles and abilities in varying domains. Frias-Martinez et al. [7] showed that the Holistic-Analytic cognitive style can be inferred when users are engaged in information seeking tasks in a digital library (accuracy over 75%). Clewey et al. [4]

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revealed that the Holism-Serialism cognitive style can be inferred when users are engaged in content exploration tasks within web-based instruction environments (accuracy over 79%). Similar findings were revealed for the FD-I cognitive style [5]. Hochberg et al. [10] revealed that the automatic annotation of Analytic-Intuitive cognitive style can be achieved when users are engaged with an image-based clinical reasoning task (accuracy over 84%). Wang et al. [34] revealed that Adaptive/Innovative and Analytic/Intuitive cognitive styles can be inferred from user-generated social media content (accuracy over 65%).

Focusing on eye-gaze based elicitation, Raptis et al. [26] revealed that FD-I cognitive style can be inferred from visual search and visual decision-making tasks (accuracy over 75%). Regarding elementary cognitive attributes (i.e., skills and abilities), Steichen et al. [29,30] performed classification experiments to classify users according to their perceptual speed, verbal and visual working memory when performing information visualization tasks; Yelizarov and Gamayunov [37] developed a mechanism to detect the users' cognitive overload and adapt the content quantity.

The discussed research endeavors lie under diverse application domains and do not consider time as a classification factor. Focusing on the user authentication domain, to the knowledge of the authors, no attempt has been made to classify users based on their cognitive characteristics using their eye-gaze data in real-time. Given existing effects of FD-I in GUA [2,14], we stress the importance of providing assistive/adaptive mechanisms in the GUA domain, and consider this work as a first step towards this vision.

USER STUDY

Research Questions

Q$_1$: Is it feasible to use real-time eye-gaze data to elicit the FD-I style when users are engaged in a graphical password composition task?

Q$_2$: Which eye-gaze metrics are most predictive for FIs and which metrics are most predictive for FDs?

Study Instruments and Metrics

Graphical User Authentication Scheme

We used *Windows™ Picture Gesture Authentication* [13], a popular and widely-used recall-based GUA scheme. The users choose a background picture and draw three gestures on it. The gestures can be any combination of circles, lines, and/or taps. The combination, the size, the position, and the direction of the drawn gestures constitute the graphical password.

Equipment

The participants created their password using a Samsung Galaxy Tab S2 (9.7" screen size with 2048x1536 pixels resolution). Their eye movements were captured using Tobii Pro Glasses 2 (50Hz). Fixations were extracted using a velocity threshold identification (I-VT) algorithm [17], based on the I-VT algorithm provided by Tobii.

Cognitive Style Elicitation Test

To elicit the participants' FD-I style, we used *Group Embedded Figures Test* (GEFT) [23], a credible and validated time-administered tool [16]. GEFT consists of 18 pattern-recognition tasks, where the users are asked to identify and outline a given pattern within a complex context, in a given amount of time. The GEFT score is the number of the correctly identified patterns; thus, the GEFT score ranges between 0 and 18. The higher the score, the more field-independent the individual is.

Eye-Gaze Metrics

Following common practice, we selected *fixation count* and *fixation duration* as suggested in [25], and *saccade length* as suggested in [8], which could provide trends in user attention patterns. For each of these basic measures, we included computed features, as discussed in [33]. For fixation count, we calculated the total number of fixations and the fixation rate. For fixation duration, we calculated the sum, mean, max, and std. deviation. For saccade length, we calculated the sum, mean, max, and std. deviation.

Classification Setup

To investigate whether it is possible to elicit FD-I in real-time, we performed a classification experiment with the discussed eye-gaze metrics. Following Toker's et al. [32] approach, we divided the activity time in time-slots of *1 second*. The time-slots start from the first second of the user's engagement with the password composition task and last until the mean time required to complete the task. In each time-slot, the users were classified either as FD or FI for each of the gaze-based metrics and their combination, and an accuracy rate (in relation to the ground-truth GEFT classification) was calculated. We also compared the classification results with those of the baseline model (i.e., all participants are classified as FDs in each time-slot according to ZeroR classifier).

Since classifications are done in consecutively increasing time-slots within the password composition task, there are cases where users complete the task in less than the mean time. We remove these users from our dataset at those time-slots, to ensure that the results are not biased, given that some metrics are correlated with time (e.g., fixation duration). Moreover, the baseline, which is based on the ZeroR classifier, is re-calculated in each time-slot.

Participants

We recruited 36 individuals (16 females) with an age range between 22 and 38 years (m=31.7; sd=6.1), of varying educational and professional background. Participants had no vision problems, had never taken a GEFT test before, and had no prior experience with GUA schemes (to avoid familiarity effects). The participants' GEFT scores were normally distributed (m=11.27, sd=3.51, p=.085). To classify each user as either FD or FI, we set the GEFT cut-off score at 12, a score that is widely used in the literature [1,27]. 17 participants were classified as FD (score: 0-11), and 19 were classified as FI (score: 12-18).

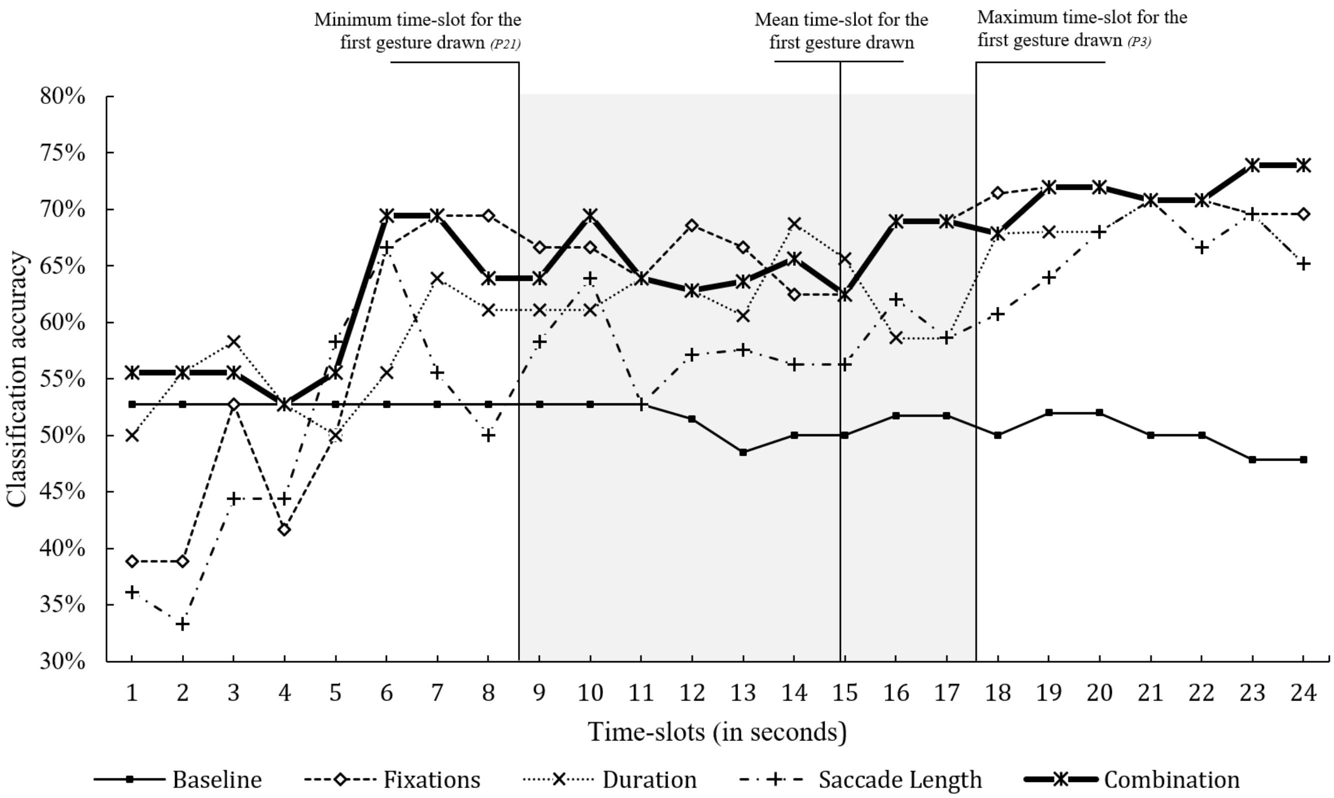

Figure 1: Classification accuracy across time-slots based on eye-gaze metrics.

Study Procedure

The study was conducted in a quiet room in our lab in one-to-one sessions and involved the following steps: *i*) the participants were introduced to the task and familiarized with the eye-tracking equipment, *ii*) we calibrated the eye-tracker following the process described in [31], *iii*) the participants used a provided background picture and drew a graphical password on it, *iv*) they completed GEFT, *v*) we asked them to log-in using their credentials to ensure they did not create the passwords randomly, and *vi*) we performed the classification experiment using the collected and calculated eye-gaze data.

RESULTS

To investigate our research questions we used WEKA software [9], following a 10-fold classification approach, mainly due to our small sample size. Regarding $\mathbf{Q_1}$, we tested several classifiers (Logistic Regression, Naïve Bayes, k-Nearest Neighbors, Classification and Regression Trees, and Support Vector Machines), towards the percentage of the correctly classified instances, with Logistic Regression (LR) providing the best results.

The results revealed that the peak accuracy was achieved towards the last time-slots (e.g., 72% accuracy for fixation count at the 19th and the 20th second). We should note that the high accuracies achieved towards the last time-slots could be due to some users completing the task in previous time-slots (e.g., the first user created the password at the 13th time-slot). Nonetheless, there was an upward trend of the combined model after the 4th second (Figure 1, Table 1).

Early prediction capabilities are of major importance for the present work, considering that the aim is to identify the user's cognitive style at the early stages of the password composition task. This will enable the delivery of suitable assistive and/or adaptive mechanisms during registration which could influence the users' decisions towards more secure and memorable passwords. Moving towards this direction, the LR classifier achieved maximum accuracies (over 63%) between the 6th and 10th time-slot and performed better than the baseline in all time-slots (apart from the 4th). The LR classifier provided the best results, regarding classification accuracy, when all the eye-gaze metrics were considered (Table 1).

Metric	Time-slot	FD	FI	Overall
Fixation count	6	12/17	12/19	66.67%
	7	12/17	13/19	69.44%
	8	11/17	14/19	69.44%
Fixation duration	7	13/17	10/19	63.89%
Saccade length	6	14/17	10/19	66.67%
Combined metrics	6	12/17	13/19	69.44%
	7	11/17	14/19	69.44%
	10	11/17	14/19	69.44%

Table 1: Maximum early prediction accuracies.

Metric	Importance	Imp. Level
Saccade length – total	100.00%	High
Fixation rate	90.30%	
Fixation duration – mean	88.81%	Moderate
Fixation duration – total	86.57%	
Saccade length – mean	85.07%	
Fixation duration – max	84.33%	
Saccade length – max	73.13%	
Fixation count – total	58.21%	Low
Saccade length – std	56.72%	
Fixation duration – std	53.73%	

Table 2: Most predictive metrics across all time-slots.

Regarding **Q_2**, we report the importance scores based on how much each metric contributes to making successful predictions. Since the classifier is constructed at each time-slot, we determine the features with the highest importance by averaging their scores across all time-slots, as in [32]. The averages are normalized so that the most important feature has a score of 100 (Table 2). Focusing on the FD-I style, our analysis on the accuracy of each class revealed that different metrics performed best for classifying the FDs and the FIs in terms of F-measure. For the classification of the FDs, the most effective metric was the saccade length (F = .795), while for the classification of the FIs, the most effective metric was the fixation count (F = .767). This could be attributed to the visual behavior differences between the FD and the FI individuals in terms of fixations and saccades, as FDs tend to produce more fixations than FIs [20,25], and they search in a more unarticulated and disoriented way [22,35], visually scanning different areas, producing saccades of larger length.

DISCUSSION

We explored the feasibility of building a classifier that identifies the user's FD-I cognitive style after collecting a few seconds of eye-gaze data during a graphical password composition task. Our classifier was based on the Logistic Regression model and outperformed the baseline classifier providing higher accuracy rates across time-slots. Focusing on the early time-slots (before the user drew the first gesture), the classifier achieved comparably similar accuracy with the accuracy towards the last time-slots.

Considering that studies have revealed effects of FD-I on password security [14] and usability [3], the classifier could be used to provide adaptive and/or assistive mechanisms for GUA schemes, such as the one described in [15], based on the individual cognitive styles elicited in real time. This could be used in combination with adaptive policies [28] to provide appropriate mechanisms for password composition and/or login. For example, given the less analytic nature of FDs, mechanisms that draw attention to overlooked areas of the background image could be used. On the other hand, given that FIs tend to pay attention to details, images could be blurred to deemphasize details and enable FIs to have a more holistic view of the image.

The results indicated that different eye-gaze metrics performed better for the FDs and the FIs, in terms of F-measure (precision and recall). Higher classification accuracy was achieved for the FDs when using the saccade length metric, whilst for the FIs when using the fixation count metric. This finding could drive the development of a mechanism based on combined classifiers, which could possibly achieve higher accuracies towards the FD-I classification. Furthermore, the classification mechanism could be complemented with more eye-gaze metrics and other interaction features to improve accuracy.

Study Validity and Limitations

Regarding internal validity, the study environment and the study procedure and instruments remained the same for all the participants. Focusing on the study instruments, we used GEFT to classify an individual as either FD or FI based on a cut-off score. Given that the GEFT test highlights cognitive differences along a continuum scale, the use of a cut-off might not classify correctly individuals that fall in between the two endpoints. However, the sample's mean GEFT score was comparable to general public scores across populations with varying demographics [1,11,16]. Regarding classification, further work towards selecting task-specific areas of interest could improve the classification accuracy. Regarding the external validity of the study, given that our approach is based mainly on eye-gaze metrics gathered and calculated in real time within a visual search task (i.e., password composition), we are positive that reasonably accurate predictions could be achieved for other visual search activities in GUA (e.g., recognition-based schemes) and other domains (e.g., gaming, automotive).

CONCLUSIONS

In this paper we investigated the feasibility of classifying users in real-time based on their FD-I style, using eye-tracking data during a graphical password composition task. Results revealed that classification is possible at the early stages of the task. Identifying the user's FD-I style early during graphical password composition could be used to introduce assistive mechanisms to help users make better password choices. The results are encouraging for further investigating various experimental designs for improving the accuracy of real-time cognitive style classifiers. A multi-level classification approach based on the combination of the FD-I most predictive metrics could be adopted during graphical password composition, to predict the users' FD-I style more accurately and assist them to create stronger and more memorable passwords.

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