On Implicit Elicitation of Cognitive Strategies using Gaze Transition Entropies in Pattern Recognition Tasks

George E. Raptis
HCI Group
Department of Electrical and Computer Engineering
University of Patras, Greece
raptisg@upnet.gr

Christos A. Fidas
Department of Cultural Heritage Management and New Technologies
University of Patras, Greece
fidas@upatras.gr

Nikolaos M. Avouris
HCI Group
Department of Electrical and Computer Engineering
University of Patras, Greece
avouris@upatras.gr

CHI'17 Extended Abstracts, May 6–11, 2017, Denver, CO, USA.
ACM ISBN 978-1-4503-4656-6/17/05.
http://dx.doi.org/10.1145/3027063.3053106

Abstract
Recent research provides evidence that individual differences on human cognitive strategies affect user performance and experience in diverse application domains. However, state-of-the-art elicitation methods of human cognitive strategies require from researchers to apply explicit, in-lab, and time-consuming "paper-and-pencil" techniques, compromising real-time integration of human cognitive strategies in interactive system design. Aiming to elaborate an implicit elicitation framework of human cognitive strategies, this paper reports on an in-lab eye-tracking study, which embraced sixty seven participants, who performed a credible "paper-and-pencil" cognitive strategy elicitation technique. Eye tracking analysis based on gaze transition entropies revealed quantitative differences on visual search patterns among individuals within visual pattern recognition tasks of varying complexity. Results of this study could drive the development of an implicit elicitation framework of human cognitive strategies.

Author Keywords
User study, Cognitive strategies; Eye tracking; Visual pattern recognition tasks.

ACM Classification Keywords
H.5. Information interfaces and presentation.

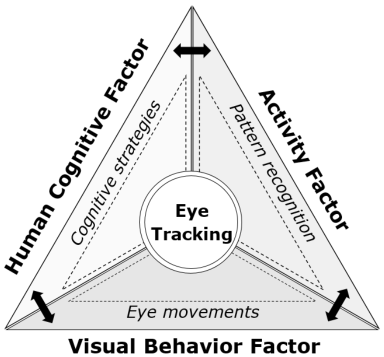


Figure 1: Eye tracking multifactorial model for implicit elicitation of human cognitive factors. It consists of three main factors: human cognitive factor (e.g., cognitive strategies), activity factor (e.g., pattern recognition activities) and visual behavior factor (e.g., eye movements).

Introduction

People differ in the way they seek, process, represent and retrieve information, as they are characterized by different cognitive attributes (e.g., skills, strategies) [14]. Recent research provides evidence that individual differences in human cognitive attributes have main effects on task performance and user experience in diverse application domains, such as e-learning [24], security [3], e-shopping [16], and gaming [20].

Tsianos et al. [24] showed that students who were characterized as visualizers (i.e., individuals who prefer pictorial content than textual) used more often media resources when interacting with an e-learning system; while verbalizers (i.e., individuals who prefer textual content than pictorial) used textual resources more often. Belk et al. [3] showed that visualizers performed better in terms of time and correct answers, when using graphical CAPTCHAs than textual ones; while verbalizers performed better when using textual CAPTCHAs. Mawad et al. [16] showed that consumers characterized as field-independent (i.e., individuals who can easily distinguish details in complex scenes) were engaged in a more thoughtful information processing, following a more analytical approach, when selecting dairy products, than field-dependent (i.e., individuals who have difficulties identifying simple information within complex scenes) consumers.

Hence, it would be beneficial to incorporate effectively cognitive strategies as human factor in personalization and adaptation frameworks, aiming to deliver real-time tailored services and functionalities, based on individual cognitive attributes. However, the barrier in such endeavors is the explicit elicitation of the cognitive strategies, which nowadays is based on traditional in-lab (e.g., "paper-and-pencil" [1,19]) and time-consuming (e.g., fifteen minutes [1,19]) techniques, compromising real-time integration of human cognitive strategies in interactive system design.

A recent literature review [21] revealed that there is a strong correlation between human cognitive attributes and visual behavior, within different types of user activities. Hence, eye-tracking tools could be used inferentially to reason about human cognitive strategies, based on quantitatively measured individual differences on visual behavior within certain types of activities. Therefore, the motivation underlying our work is moving toward an implicit elicitation framework of cognitive strategies, based on an *eye-tracking multifactorial model* of: human cognitive factor, visual behavior factor, and activity factor (as depicted in Figure 1). From a methodological perspective, such a framework should rely on ground-truth data derived from state-of-the-art, credible, and validated tools used for cognitive strategies elicitation.

This paper reports a feasibility study to justify the use of the aforementioned multifactorial model to design an eye-tracking framework to elicit human cognitive strategies implicitly and in real time. Our study was based on *Group Embedded Figures Test (GEFT)* [11,19], a traditional "paper-and-pencil" instrument. GEFT is used to classify individuals according to *Field Dependence – Independence (FD-I)* cognitive strategy [26]; one of the most well established, credible and validated [2,4] cognitive strategy frameworks. GEFT is a time-administered tool which consists of a set of pattern recognition tasks of diverse complexity, in which the users are asked to identify simple shapes within complex figures.

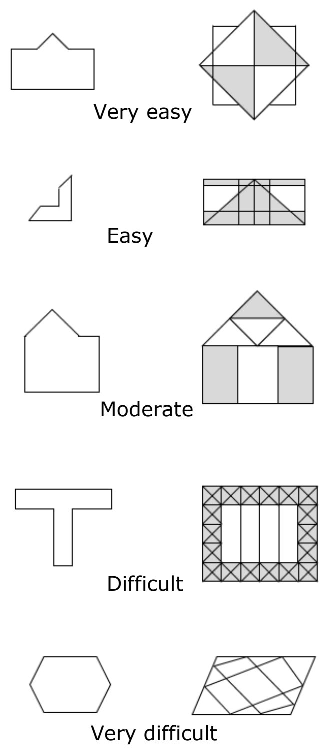


Figure 2: Samples of the pattern recognition tasks [9]. The users were asked to identify and outline the simple form (left figure) into the complex one (right figure). The tasks differ in terms of difficulty, starting from very easy (top figure) to very difficult (bottom figure).

Related Work

To the authors' knowledge there are no studies which follow the framework proposed in Figure 1, which incorporates its three main factors to propose an implicit elicitation mechanism of cognitive strategies. Despite that a number of studies have shown a strong correlation among eye movements, cognitive strategies and pattern recognition tasks [5,10,17,18], none of them has elaborated on an implicit elicitation framework of cognitive strategies. Nisiforou and Laghos [18] investigated the association between FD-I and eye movements within visual search tasks, and they found significant differences among field dependents and field independents in terms of low-level eye-tracking metrics (e.g., number of fixations and saccades). However, the visual strategy (e.g., scanpaths) the users followed was discussed only qualitatively, and despite the insights we gained, such non-quantitative analysis could not be used by information systems to elicit human cognitive factors implicitly in in-real time scenarios.

Theoretical Background

Human Cognitive Factor

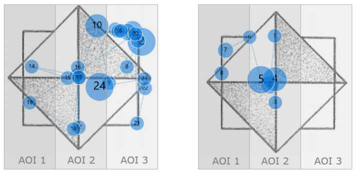
The theoretical background of this work is based on the three axes of the multifactorial model (Figure 1). The human cognitive factor reflects on theories of individual differences in cognitive strategies, suggesting that individuals have preferred ways of seeking, representing, processing and retrieving information, which are related to their individual cognitive skills and abilities, e.g. perceptual speed and memory load [6,12,26]. Several researchers have focused on high-level cognitive processes to explain empirically such observed differences [14]. Such processes are called *cognitive strategies* and a number of them has been developed and studied over the years [1,12,22,26].

One of the most well established, credible and validated [2,4] cognitive strategies is the *Field Dependence-Independence (FD-I)* style [26], which classifies people as field dependent (FD) or field independent (FI). FDs tend to prefer a more holistic way when processing information, and have difficulties in identifying visual details in complex scenes [26]. 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 context [26].

Visual Behavior Factor

As FD-I is based on visual tasks performance, it is related to visual perception (i.e., the ability to identify, organize, and interpret the environment by processing visual information). Visual perceptual span varies in visual search tasks, depending on the difficulty level of the task and it is interrelated with eye movements [27]. Eye movement data is captured through eye-tracking tools, helping us understand individuals' visual behavior, and the strategy they follow to solve visual problems. The recent technological advances have had a major impact on the eye-tracking industry, with the development of devices of high accuracy. A number of eye-tracking data and measures of diverse complexity have been developed, such as number of fixations and saccades, fixation duration[7], trending scan-path analysis [8], and transition entropies [15].

A high-level eye-tracking measure used to quantify the visual search strategy is the *gaze transition entropy* proposed by Krejtz et al. [15]. 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 the areas of interest (AOIs) of a stimuli, and the stationary



	AOI 1	AOI 2	AOI 3
AOI 1	67%	22%	11%
AOI 2	10%	70%	20%
AOI 3	25%	50%	25%

	AOI 1	AOI 2	AOI 3
AOI 1	50%	50%	0%
AOI 2	100%	0%	0%
AOI 3	0%	100%	0%

Figure 3: 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. Lower H_t and H_s are displayed on the right figure.

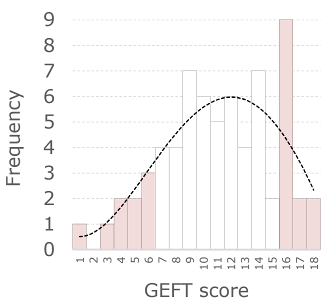


Figure 4: Participants' GEFT scores were normally distributed (Shapiro-Wilk: p=0.145). The light-red areas indicate the extreme FDs (left side) and the extreme FIs (right side).

distribution of eye-movements over the stimuli, 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.

Activity Factor

A recent literature review [21] revealed that activity types (e.g., visual exploration, visual search, pattern recognition) influence visual behavior. Since FD-I measures the ability of individuals to identify simple details in complex visual scenes, it reflects on pattern recognition activity type. The traditional FD-I elicitation tool (i.e., GEFT) consists of twenty-five pattern recognition tasks of varying complexity. For each task, individuals are asked to identify and outline a simple figure within a complex one. The test consists of three sections of seven, nine and nine items, with two, five and five minutes allocated respectively. The number of simple figures correctly identified on the last two sections constitutes the raw score, which is used to classify the subject as FD or FI (i.e., the higher the score, the more field-independent the subject is).

Tasks differ in terms of difficulty and complexity; factors that affect the performance of individuals with different cognitive attributes [23,27]. The FD-I pattern recognition tasks span across five difficulty states: very easy, easy, medium, difficult and very difficult [9,25]. The classification of each task was based on the time needed by a sample of individuals to correctly solve the task and the total number of errors made, according to the original work of Gottschaldt [9] and Witkin [25]. A sample set of tasks is depicted in Figure 2.

User study

Participants

Sixty-seven subjects (29 females, 38 males), ranging in age from 20 to 47 (31.1 ± 6.4), participated in the experiment. Each participant undertook GEFT, and their score ranged from 1 to 18 (11.4 ± 3.7) (Figure 4).

Apparatus

Participants' eye movements were recorded with Tobii Pro Glasses 2 wearable system. Following common practice, we focused on where and when fixations occurred. Fixations were extracted using a customized velocity threshold identification (I-VT) algorithm [13], based on the I-VT algorithm provided by Tobii.

Hypotheses

The following null hypotheses were formed: $H0_1$: there is no significant difference between FDs and FIs in terms of gaze transition entropy H_t throughout visual pattern recognition tasks of specific difficulty. $H0_2$: there is no significant difference between FDs and FIs in terms of gaze stationary entropy H_s throughout visual pattern recognition tasks of specific difficulty.

Procedure

At first, we recruited the study participants, who had to meet a set of minimum requirements (i.e., have never taken GEFT before, be older than 18 years old, and have no vision problems). Then, each participant was allocated with a wearable eye-tracking device and was asked to undertake the original GEFT tasks. Afterwards, the analysis of the results followed.

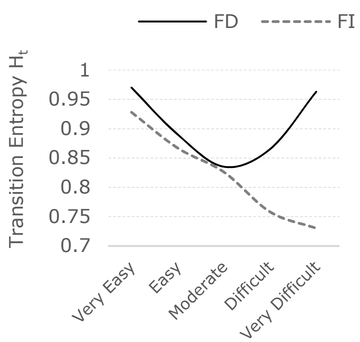


Figure 5: FI individuals produced more gaze transitions among AOIs (expressed in transition entropy H_t) than FDs. Their difference increases as the task complexity increases.

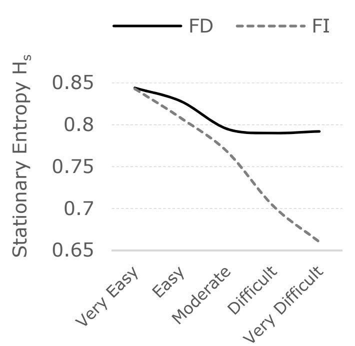


Figure 6: FD individuals distributed their attention more equally among AOIs (expressed in stationary entropy H_s) than FIs; the difference increases as the task complexity increases.

Analysis of Results and Interpretation

The analysis of the eye movement data focuses on the comparison of participants' visual search strategy (in terms of transition and stationary entropies) in relation to their cognitive group and the difficulty level of each pattern recognition task. For the scope of the study, 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 FDs (i.e., individuals who scored lower than 7) and 13 FIs (i.e., individuals who scored higher than 15). Moreover, each complex form of the pattern recognition task was divided into three vertical AOIs (Figure 3), as it was originally performed in Krejtz et al. [15] study. For each entropy type, we performed a within-subjects 2x5 ANOVA, with cognitive strategy (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.

Gaze transitions among AOIs

The 2x5 ANOVA test met all assumptions (i.e., there were no outliers; H_t was distributed normally; H_t variance was homogenous). The results indicated that there was a statistically significant interaction effect between cognitive strategy and visual search task difficulty for transition entropy H_t ($F=6.212$, $p<0.005$, partial $\eta^2=0.430$). 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 ($F=8.270$, $p=0.007$, $\eta^2=0.200$ for difficult tasks, and $F=38.685$, $p=0.001$, $\eta^2=0.540$ 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 (Figure 5).

Visual attention distribution on AOIs

The 2x5 ANOVA test met all assumptions (i.e., there were no outliers; H_s was distributed normally; H_s variance was homogenous). The results indicated that there was a statistically significant interaction effect between cognitive strategy and visual search task difficulty for stationary entropy H_s ($F=3.406$, $p=0.019$, partial $\eta^2=0.292$). 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 ($F=7.878$, $p=0.038$, $\eta^2=0.193$ for difficult tasks, and $F=18.752$, $p=0.001$, $\eta^2=0.362$ for very difficult tasks). A higher value of stationary entropy means that the subject distributes their visual attention more equally among AOIs. A lower value is obtained when fixations tend to be concentrated on certain AOIs (Figure 6).

Both findings indicate that individuals who have different cognitive strategies, 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 score of GEFT. That is, the significant differences in transition and stationary entropies, when performing difficult and very difficult pattern recognition tasks, are in-line with FDs' and FIs' differences in task performance, in terms of completion time and correct answers (Figures 7 and 8).

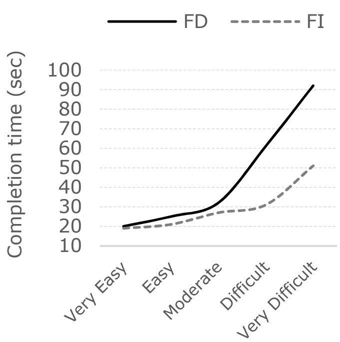


Figure 7: FDs need more time to identify simple figures within complex ones, on pattern recognition tasks, than FIs. Their difference, in terms of completion time, increases as the task complexity increases.

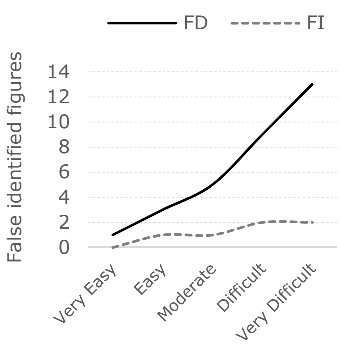


Figure 8: FDs made more mistakes on pattern recognition tasks, than FIs. Their difference, in terms of false identified figures, increases as the task complexity increases.

Implications for further research

Based on the derived results, an implicit elicitation framework, based on eye-tracking, is proposed (Figure 9). It reflects on the multifactorial model (Figure 1) components (i.e., human cognition, visual behavior and activity factors). It consists of three layers: *knowledge*, *data acquisition*, and *implicit elicitation*. Each layer has discrete functionalities and is expandable.

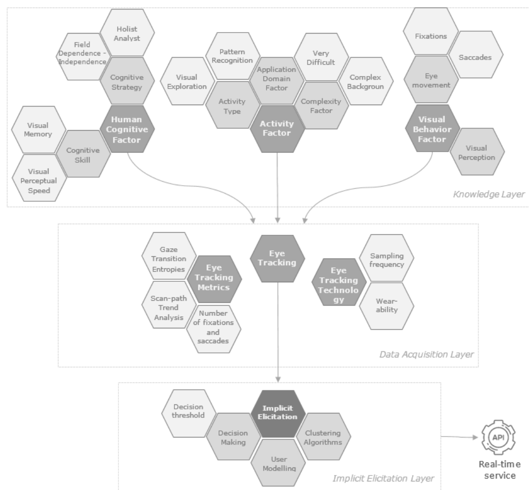


Figure 9: Implicit elicitation framework of human cognitive attributes, based on eye-tracking.

The *knowledge layer* contains data which reflect the interplay among human cognition, visual behavior, and activity factors. Knowledge data should be continuously enriched and refined from credible and validated research studies.

The *data acquisition* layer continuously collects data derived from eye-tracking device and correlates the gathered data with the knowledge of the framework for specific activity, visual behavior and desired human cognitive factors to be implicitly elicited.

The *implicit elicitation* layer reasons about the human cognitive factors by classifying individuals based on a decision making approach. It would rely on probabilistic methods, based on threshold analysis and cut-off score techniques, to model user behaviors and provide the classification decision to third-party service providers.

An example of future use of the proposed framework is in action games, which entail information processing tasks. Gamers would wear mixed reality glasses to visually scan gaming context and search for assets to complete game objectives. The integrated eye-tracking tool would be used to elicit gamers' cognitive strategies implicitly and in-real time, providing them with personalized experiences, and adapting the gaming environment to their preferences automatically by adjusting the game difficulty level accordingly.

Conclusion

This paper revealed that individual differences in cognitive strategies are quantitatively reflected on gaze transitions in specific visual pattern recognition tasks of varying complexity. Bearing in mind that the presented results relied on a ground-truth and credible method for human cognitive strategies elicitation, such research endeavors could drive an elaboration of an implicit elicitation framework of human cognitive strategies, based on eye-tracking data. We also presented initial ideas of such a framework. Real-time and implicit elicitation of human cognitive strategies would open unprecedented opportunities for improving user experience through adaptation and personalization, on a plethora of application and research domains.

References

1. Christopher W. Allinson and John Hayes. 1996. The Cognitive Style Index: A Measure of Intuition-Analysis For Organizational Research. *Journal of Management Studies* 33, 1: 119–135. http://dx.doi.org/10.1111/j.1467-6486.1996.tb00801.x.
2. Charoula Angeli, Nicos Valanides, and Paul Kirschner. 2009. Field dependence–independence and instructional-design effects on learners' performance with a computer-modeling tool. *Computers in Human Behavior* 25, 6: 1355–1366. http://dx.doi.org/10.1016/j.chb.2009.05.010.
3. Marios Belk, Christos Fidas, Panagiotis Germanakos, and George Samaras. 2015. Do human cognitive differences in information processing affect preference and performance of CAPTCHA? *International Journal of Human-Computer Studies* 84: 1–18. http://dx.doi.org/10.1016/j.ijhcs.2015.07.002.
4. Dane M Chapman and Judith G Calhoun. 2006. Validation of learning style measures: implications for medical education practice. *Medical Education* 40, 6: 576–583. http://dx.doi.org/10.1111/j.1365-2929.2006.02476.x.
5. Rodney C. Conklin, Walter Muir, and Frederick J. Boersma. 1968. Field Dependency-Independency and Eye-Movement Patterns. *Perceptual and Motor Skills* 26, 1: 59–65. http://dx.doi.org/10.2466/pms.1968.26.1.59.
6. Andreas Demetriou, George Spanoudis, Michael Shayer, Antigoni Mouyi, Smaragda Kazi, and Maria Platsidou. 2013. Cycles in speed-working memory-G relations: Towards a developmental–differential theory of the mind. *Intelligence* 41, 1: 34–50. http://dx.doi.org/10.1016/j.intell.2012.10.010.
7. Andrew T. Duchowski. 2007. *Eye tracking methodology: Theory and practice*. Springer London, London, UK.
8. Sukru Eraslan, Yeliz Yesilada, and Simon Harper. 2016. Eye tracking scanpath analysis on web pages. *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications - ETRA '16*, ACM Press, 103–110. http://dx.doi.org/10.1145/2857491.2857519.
9. Kurt Gottschaldt. 1938. Gestalt factors and repetition. In *A source book of Gestalt psychology.* Kegan Paul, Trench, Trubner & Company, London, 109–135. http://dx.doi.org/10.1037/11496-009.
10. Christian Gütl, Maja Pivec, Christian Trummer, et al. 2005. Adele (adaptive e-learning with eye-tracking): Theoretical background, system architecture and application scenarios. *European Journal of Open, Distance and E-Learning* 8, 2.
11. Mohammad Khatib and Rasoul Mohammad Hosseinpur. 2011. On the Validity of the Group Embedded Figure Test (GEFT). *Journal of Language Teaching and Research* 2, 3. http://dx.doi.org/10.4304/jltr.2.3.640-648.
12. Michael Kirton. 1976. Adaptors and innovators: A description and measure. *Journal of Applied Psychology* 61, 5: 622–629. http://dx.doi.org/10.1037/0021-9010.61.5.622.
13. Oleg V Komogortsev, Denise V Gobert, Sampath Jayarathna, Do Hyong Koh, and Sandeep M Gowda. 2010. Standardization of Automated Analyses of Oculomotor Fixation and Saccadic Behaviors. *IEEE Transactions on Biomedical Engineering* 57, 11: 2635–2645. http://dx.doi.org/10.1109/TBME.2010.2057429.
14. Maria Kozhevnikov. 2007. Cognitive styles in the context of modern psychology: Toward an integrated framework of cognitive style. *Psychological Bulletin* 133, 3: 464–481. http://dx.doi.org/10.1037/0033-2909.133.3.464.
15. Krzysztof Krejtz, Andrew Duchowski, Tomasz Szmidt, et al. 2015. Gaze Transition Entropy. *ACM Transactions on Applied Perception* 13, 1: 1–20. http://dx.doi.org/10.1145/2834121.
16. Franco Mawad, Marcela Trías, Ana Giménez, Alejandro Maiche, and Gastón Ares. 2015. Influence of cognitive style on information

processing and selection of yogurt labels: Insights from an eye-tracking study. *Food Research International* 74: 1–9. http://dx.doi.org/10.1016/j.foodres.2015.04.023.

17. Efi A. Nisiforou and Andrew Laghos. 2013. Do the eyes have it? Using eye tracking to assess students cognitive dimensions. *Educational Media International* 50, 4: 247–265. http://dx.doi.org/10.1080/09523987.2013.862363.

18. Efi Nisiforou and Andrew Laghos. 2016. Field Dependence–Independence and Eye Movement Patterns: Investigating Users' Differences Through an Eye Tracking Study. *Interacting with Computers* 28, 4: 407–420. http://dx.doi.org/10.1093/iwc/iwv015.

19. Philip K Oltman, Evelyn Raskin, and Herman A. Witkin. 1971. *Group Embedded Figures Test*. Consulting Psychologists Press, Palo Alto CA, USA.

20. George E. Raptis, Christos A. Fidas, and Nikolaos M. Avouris. 2016. Do Field Dependence-Independence Differences of Game Players Affect Performance and Behaviour in Cultural Heritage Games? *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '16*, ACM Press, 38–43. http://dx.doi.org/10.1145/2967934.2968107.

21. George E. Raptis, Christos A. Fidas, and Nikolaos M. Avouris. 2016. Using Eye Tracking to Identify Cognitive Differences: A Brief Literature Review. *20th Pan-Hellenic Conference in Informatics*. http://dx.doi.org/10.1145/3003733.3003762.

22. Richard Riding and Indra Cheema. 1991. Cognitive Styles—an overview and integration. *Educational Psychology* 11, 3-4: 193–215. http://dx.doi.org/10.1080/0144341910110301.

23. Dereck Toker, Cristina Conati, Ben Steichen, and Giuseppe Carenini. 2013. Individual user characteristics and information visualization. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '13*, ACM Press, 295. http://dx.doi.org/10.1145/2470654.2470696.

24. Nikos Tsianos, Panagiotis Germanakos, Zacharias Lekkas, Costas Mourlas, and George Samaras. 2009. Eye-Tracking Users' Behavior in Relation to Cognitive Style within an E-learning Environment. *2009 Ninth IEEE International Conference on Advanced Learning Technologies*, IEEE, 329–333. http://dx.doi.org/10.1109/ICALT.2009.110.

25. Herman A. Witkin. 1950. Individual Differences in Ease of Perception of Embedded Figures. *Journal of Personality* 19, 1: 1–15. http://dx.doi.org/10.1111/j.1467-6494.1950.tb01084.x.

26. Herman. A. Witkin, Carol A. Moore, Donald R. Goodenough, and Patricia W. Cox. 1975. Field-Dependent and Field-Independent Cognitive Styles and their Educational Implications. *ETS Research Bulletin Series* 1975, 2: 1–64. http://dx.doi.org/10.1002/j.2333-8504.1975.tb01065.x.

27. Peter Wittek, Ying-Hsang Liu, Sándor Darányi, Tom Gedeon, and Ik Soo Lim. 2016. Risk and Ambiguity in Information Seeking: Eye Gaze Patterns Reveal Contextual Behavior in Dealing with Uncertainty. *Frontiers in Psychology* 7. http://dx.doi.org/10.3389/fpsyg.2016.01790.