

ASSESSING THE IMPORTANCE OF COGNITIVE LEARNING STYLES OVER PERFORMANCE IN MULTIMEDIA EDUCATIONAL ENVIRONMENTS

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ABSTRACT

The aim of this paper is to introduce the “new” user profiling dimensions [1] that incorporate other than the “traditional” user characteristics, focusing on what we refer to as “user perceptual preference characteristics”. These characteristics consist of cognitive and emotional traits, which define a unique, for each user, information processing and learning procedure. We discuss some primary adaptive hypermedia design considerations and emphasize on vital adaptivity characteristics and implications in the information space. This paper also defines an Adaptive Web-based Educational System incorporating the aforementioned “new” user profiling. In support of these concepts, it lastly presents results of experiments taken place at the Laboratory of New Technologies of the University of Athens, assessing the importance of specific cognitive learning styles and adaptation techniques on Web-based multimedia content delivery systems.

Key Words: adaptive hypermedia, user profiling, learning styles

1. Introduction

Adaptivity is a particular functionality that alleviates navigational difficulties by distinguishing between interactions of different users within the information space [2,3]. Adaptive Hypermedia Systems employ adaptivity by manipulating the link structure or by altering the presentation of information, based on a basis of a dynamic understanding of the individual user, represented in an explicit user model [4,5,6,7,8]. In the 1997 discussion

forum on Adaptive Hypertext and Hypermedia, an agreed definition of adaptive hypermedia systems was reached after Brusilovsky [9] as follows: “By Adaptive Hypermedia Systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible and functional aspects of the system to the user.” [10,11]. A system can be classified as an Adaptive Hypermedia System if it is based on hypermedia, has an explicit user model representing certain characteristics of the user, has a domain model which is a set of relationships between knowledge elements in the information space, and is capable of modifying some visible or functional part of the system based on the information maintained in the user model [12,13,14].

In further support of the aforementioned concept of adaptivity, one cannot disregard the fact that, besides the parameters that constitute the traditional user profile (such as age, demographics, experience etc), each user carries his own perceptual and cognitive characteristics that have a significant effect on how information is perceived and processed. Information is encoded in the human brain by triggering electrical connections between neurons, and it is known that the number of synapses that any person activates each time is unique and dependant on many factors, including physiological differences [15]. Since early work on the psychological field has shown that research on actual intelligence and learning ability is hampered by too many limitations, there have been a “number of efforts to identify several styles or abilities and dimensions of cognitive and perceptual

processing” [16], which have resulted in what is known as learning and cognitive styles. *Learning and cognitive styles* can be defined as relatively stable strategies, preferences and attitudes that determine an individual’s typical modes of perceiving, remembering and solving problems, as well as the consistent ways in which an individual memorizes and retrieves information [17]. Each learning and cognitive style typology defines patterns of common characteristics and implications in order to overcome difficulties that usually occur throughout the procedure of information processing. Therefore, in any knowledge distributing environment, the significance of the fore mentioned users’ differences, both physiological and preferential, is distinct and should be taken under consideration when designing such adaptive environments.

2. The “New” User Profiling

Based on the abovementioned considerations we introduce the “New” User Profiling that combines the User Perceptual Preference Characteristics described above along with the “Traditional” User Profiling Characteristics since they are affecting the way a user approaches an object of perception.

The “New” User Profiling could be considered as the main raw content filtering module of an Adaptive Web-based Multimedia Architecture. At this module all requests are processed, custom tailoring the information to be delivered to users, taking into consideration their habits and preferences, as well as, for mobile users mostly, their location (“location-based”) and time (“time-based”) of access [18]. The whole processing varies from security, authentication, user segmentation, educational content identification, user perceptual characteristics (visual, cognitive and emotional processing parameters) and so forth. This module could accept requests from an ‘Entry Point’, and after the necessary processing and further communication with a ‘Semantic Web-based Multimedia Content’ module, could provide the requested adapted and personalized result. The “New” User Profiling is comprised of two main components:

2.1 The “Traditional” User Profile

It contains all the information related to the user, necessary for the Web Personalization processing. It is composed of two elements, the (a) *User Characteristics* (the so called “traditional” characteristics of a user: knowledge, goals, background, experience, preferences, activities, demographic information (age, gender), socio-economic information (income, class, sector etc.), and the (b) *Device / Channel Characteristics* (contains characteristics that referred to the device or channel the user is using and contains information like: Bandwidth, displays, text-writing, connectivity, size, power processing, interface and data entry, memory and storage space, latency (high / low), and battery lifetime. Both elements are completing the user profiling from the user’s point of view.

2.2 User Perceptual Preference Characteristics

This is the new component / dimension of the user profiling defined above. It contains all the visual attention and cognitive psychology processes (cognitive and emotional processing parameters) that complete the user profile. User Perceptual Preference Characteristics could be described as a continuous mental processing starting with the perception of an object in the user’s visual field of attention, undergoing a number of cognitive, learning and emotional processes giving the actual response to that stimulus. As it can be observed, its primary parameters formulate a **three-dimensional** approach to the problem:

(a) *Visual & Cognitive Processing*: From the *Visual Processing* aspect, special emphasis is given at tracking the user’s eye movements, and in particular scanning his / her eye gaze on the information environment. There are two distinct serial phases: the pre-attentive and the limited-capacity stage. The pre-attentive stage of vision subconsciously defines objects from visual primitives, such as lines, curvature, orientation, color and motion and allows definition of objects in the visual field. When items pass from the pre-attentive stage to the limited-capacity stage, these items are considered as selected. Interpretation of eye movement data is based on the empirically validated assumption that when a person is performing a cognitive task, while watching a display, the location of his / her gaze

corresponds to the symbol currently being processed in working memory and, moreover, that the eye naturally focuses on areas that are most likely to be informative. *Cognitive Processing* parameters could be primarily determined by (i) the **control of processing** (refers to the processes that identify and register goal-relevant information and block out dominant or appealing but actually irrelevant information), (ii) the **speed of processing** (refers to the maximum speed at which a given mental act may be efficiently executed), and (iii) the **working memory** (refers to the processes that enable a person to hold information in an active state while integrating it with other information until the current problem is solved). Many researches [19,20] have identified that the speed of cognitive processing and control of processing it is directly related to the human's age, as well as to the continuous exercise and experience, with the former to be the primary indicator. Therefore, the processing development speed increases non-linearly in the age of 0 – 15 (1500 m/sec), it is further stabilized in the age of 15 - 55-60 (500 m/sec) and decreases from that age on (1500 m/sec). However, it should be stated that the actual cognitive processing speed efficiency is yielded from the difference (maximum value 0.8 m/sec) between the peak value of the speed of processing and the peak value of control of processing.

(b) *Learning Styles*: They represent the particular set of strengths and preferences that an individual or group of people have in how they take in and process information. A selection of the most appropriate and technologically feasible learning styles are taken into consideration, such as Witkin's Field-Dependent and Field-Independent [21], Riding's Cognitive Style Analysis (Verbal-Imager and Wholistic-Analytical) [22], and Kolb's Learning Styles (Converger, Diverger, Accomodator, and Assimilator) [23], being in a position to identify how users transforms information into knowledge (constructing new cognitive frames).

(c) *Emotional State*: The whole emotional processing of a user's interaction with the information space consists of these parameters that could determine his / her emotional state during the response process. This is vital so as to determine whether the user is in an

emotional state that would allow information processing and learning. We intend to incorporate some form of filtering at the entry point of the web- application, such as a Depression- Anxiety- Stress questionnaire, in order to identify an abnormal state that would hamper the learning process.

3. The “New” User Profiling Construction

Taking a closer look to the “New” User Profiling Construction system, the user enters the Web-Application with a unique access code and has to give particular information (Traditional profiling component development) as well as to pass through a series of tests (others in the form of questionnaires and others with real time interaction metrics) through of which information with regards to the User Perceptual Preference Characteristics described above will be extracted. The data collected from both components will be stored and transferred in the form of XML documents. For a better insight, the Tree Structure of the “New” User Profiling, giving emphasis on the “new” user profile structure.

At the application-server tier all the calculations such as the user categorization and mapping, content reconstruction and content adaptation will take place. In order for the latter to run properly Web-based multimedia content is conveyed from the provider's application in the form of metadata.

Once the provided content adjusted based on the developed rules to the user characteristics it returns the corresponding adapted and personalized result. It has also to be mentioned that there is a continuous communication with the Database-server where all the data are stored.

4. Experimental Implementation Considerations based on Related Cognitive Notions

In order to assess the aforementioned importance of learning and cognitive styles over performance in multimedia environments, we designed an experiment on the field of adaptive e-learning [24]. Our main goals were:

- To prove that web-based environments that usually match the learning / cognitive style of their designers instead of users', in a probably random way, may result in limiting the information retaining capability of those whose learning style mismatches the one implemented, while others may be benefited from this random match.
- To seek out ways of implementing learning/ cognitive style theories into web-based multimedia or hypermedia content delivery systems.

We chose to experiment on an e-learning multimedia environment because of the increased interest on distant education via the web, not to mention the challenges of adaptation over non-interpersonal educative procedures. Moreover, in this case we were able to control factors as previous knowledge and experience over distributed information, by integrating this e-learning procedure into an undergraduate course on algorithms at our department, where 1st year students have absolutely no background and traditionally perform poor.

In order to classify students according to their learning style, we used the Felder / Soloman Index of Learning Styles (ILS) [25]. Since our sample consisted of 70 undergraduate students from our department, we decided to use this specific tool because it is suitable and convenient for educational environments. Even more importantly, ILS not only classifies students in distinct types, but indicates the strength of each person's preference on the scale (low, medium, high). In a wider field, we would have proposed Riding's Cognitive Style Analysis, which applies in a greater number of information distribution circumstances, since it deals rather with cognitive than learning style. Still, considering circumstantial and convenience factors, we used the ILS.

The Felder/ Silverman theory [26] distinguishes 4 independent scales that measure certain aspects of the learning process: Active vs Reflective, Sensing vs Intuitive, Visual vs Verbal, Sequential vs Global.

We noticed that our subjects demonstrated a considerably higher variation in the Sensing-Intuitive scale. As a result, we focused on that

dimension, expecting to see noticeable differences in their information retaining (or learning) performance, depending on how intuitive or sensing the students are.

Consequently, we designed a multimedia e-learning environment that teaches algorithms in an intuitive manner. The selection of this subject and content was based on the abovementioned subjects' poor performance due to lack of appropriate background. Our subjects participated in this e-learning course, instead of undergoing conventional teaching methods, and as soon as the learning procedure ended, they took an on-line exam to assess what they had learned.

4.1 Results

The results of our experiment, as indicated by the students' performance on the on-line exams regarding their learning style, seem to confirm our initial expectations. In general terms, students whose learning style, according to Felder typology, was "intuitive" achieved higher scores than those whose learning style didn't match the teaching style implemented in our web-based multimedia content- delivery environment. First of all, considering the match/ mismatch factor, results showed that average performance for intuitive students was 87%, while sensing students averaged 75.3%. Overall average was 80.2%. When computing average scores between types, we take into account medium or high intuitive/sensing students, excluding intermediates scorers on the Felder/ Soloman questionnaire, because low scorers and intermediates of each scale do not require adaptation to their learning style since they do not exhibit any specific preference.

4.1.1 Overall results (N=70)

We found that the score that each subject achieved on the Index of Learning Styles sensing/ intuitive scale was significantly correlated with his/ her performance on the exams. Those with a negative score on the SI scale (ranging from -1 to -11) were the intuitive ones, while positive score indicated that the subject was sensing. As expected, there was a negative correlation between the SI scale and the exams' Score, since negative score on the SI scale (therefore intuitive style) resulted in higher score (see Table 1).

		Sensing-Intuitive	SCORE
Sensing-Intuitive	Spearman's rho	1	-,349**
	Sig. (1-tailed)	,	,002
	N	70	70

** Correlation is significant at the 0.01 level (1-tailed)

Table 1. Correlation of Intuition with Score

Correlation with the Active- Reflective and Visual- Verbal scale was indeed insignificant, since we kept a balance in the implications of these factors in the design of our multimedia environment.

However, we noticed a correlation of some significance between the Sequential/ Global scale and the score. Although navigation could be performed both in a sequential and a global manner, global students did better than sequential. This can be explained due to the fact that many intuitive students were also global, as indicated by the highly significant correlation between the SI and the SQ scales.

4.1.2 Medium and extreme scorers' on the ILS results (N=32)

If we take into account only those with a higher need of adaptation on the content that is delivered through web-based multimedia systems, according to cognitive and learning style theories, the individual way that each person processes information seems to be even more important (see Table 2).

		Sensing-Intuitive	SCORE
Sensing-Intuitive	Spearman's rho	1	-,501**
	Sig. (1-tailed)	,	,002
	N	32	32

** Correlation is significant at the 0.01 level (1-tailed)

Table 2. Correlation of Intuition with Score, when referring to subjects that require adaptation on their learning style

It becomes evident that when we limit the number of our sample to medium and high sensing/ intuitive students, correlation with score becomes even higher (-0.501 instead of -0,349). This fact confirms Felder's theory that stronger preference to a specific learning style

mediates information processing in more crucial manner, and consequently leads to greater need of adaptation.

4.2 Qualitative remarks

Out of 70 students, only 15 subjects managed to answer correctly on all of the questions featured on the exams, therefore scoring 100%, though the difficulty of the questions was rather low. None of them was medium or high sensing. More specifically: 4 were highly intuitive, 2 were medium intuitive, 5 were low intuitive, 2 were intermediates and 2 were low sensing.

In other words, 73% were intuitive at some extent, while, in contrast, only 13% of those with a 100% score were sensing. This reinforces the importance of the match/ mismatch of learning or cognitive style factor. Amongst those who had an above average score, 50% were intuitive, 31% intermediates and 19% sensing. Accordingly, of those who scored below average, 52% were sensing, 33% were intermediates and 19% intuitive.

Even though it is a rather complicated procedure to accurately assess the impact of learning style over performance in a multimedia environment, we do have some rather clear indications that when learning or cognitive style is taken under consideration, information processing and retaining, which is a key element in assessing web-based environments, is reinforced, whilst limitations of style mismatch can be limited.

5. Conclusion

This paper made an extensive reference to the adaptation of Web-based multimedia content delivery investigating delivery characteristics of user-centered multimedia content and the adaptation and personalization considerations with regards to new user requirements and demands. It underpinned the significance of the user profiling introducing the "new" comprehensive user profiling that incorporates intrinsic user characteristics such as user perceptual preferences. In further support of the above concepts we presented experimental results of an Adapted e-Learning Multimedia Content Environment that considers cognitive learning styles as its main personalization filter. With this experiment we do have some

rather clear indications that when learning or cognitive style is taken under consideration information processing and retaining is reinforced. Therefore, a profile can be considered complete when it incorporates the users' perceptual preference characteristics that mostly deal with intrinsic parameters.

In our future work we will study in depth the role of emotions in the learning process, especially in terms of emotional control. We will also focus on the structure of the metadata coming from the providers' side, aiming to construct a Web-based personalization system that will serve as an automatic filter, adapting the Web- content on the basis of the "new" comprehensive user profiling. We will further study security issues related to user profiling and we will build a Web-based educational multimedia environment that will prove the validity of our approach.

6. References

- [1] Germanakos, P., Tsianos, N., Mourlas, C., Samaras, G., 2005, New Fundamental Profiling Characteristics for Designing Adaptive Web-based Educational Systems. Proceeding of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age (CELDA2005), Porto, December 14-16, 2005, pp. 10-17.
- [2] Eklund, J. and Sinclair, K., 2000, An empirical appraisal of the effectiveness of adaptive interfaces of instructional systems. *Educational Technology and Society* 3 (4), ISSN 1436-4522.
- [3] Brusilovsky, P. and Nejdil, W., 2004. Adaptive Hypermedia and Adaptive Web. © 2004 CSC Press LLC.
- [4] Eklund, J. and Sinclair, K., o.p.
- [5] De Bra, P., Brusilovsky, P. and Houben, G., 1999. Adaptive Hypermedia: From systems to framework. *ACM Computing Surveys* 31(4).
- [6] Brusilovsky, P., 2001. Adaptive Hypermedia, User Modeling and User-Adapted Interaction 11: 87-110.
- [7] Brusilovsky, P., 1996a Adaptive Hypermedia: an attempt to analyse and generalize, In P. Brusilovsky, P. Kommers, & Streitz (Eds.), *Multimedia, Hypermedia, and Virtual Reality*, Berlin: Springer-Verlag, 288-304.
- [8] Brusilovsky, P., 1996b Methods and techniques of adaptive hypermedia. *User Modeling and User Adapted Interaction*, 1996, v6, n 2-3, pp 87-129.
- [9], [10], Eklund, J. and Sinclair, K., o.p.
- [11] Brusilovsky, P., 1996b, o.p.
- [12] Eklund, J. and Sinclair, K., o.p.
- [13] Brusilovsky, P. and Nejdil, W., o.p.
- [14] Brusilovsky, P., 1996b, o.p.
- [15] Graber, D., A., 2000. *Processing Politics*. Chapter 2, The University of Chicago Press, 2000.
- [16] McLoughlin, C., 1999. The implications of the research literature on learning styles for the design of instructional material. *Australian Journal of Educational Technology*, 1999, 15(3), p. 222-241.
- [17] Pithers, R., T., 2002. Cognitive Learning Style: a review of the field dependent- field independent approach, *Journal of Vocational Education and Training*, Volume 54, Number 1, 2002, p. 117-8.
- [18] Panayiotou, C., and Samaras, G. mPersona: Personalized Portals for the Wireless User: An Agent Approach. *Journal of ACM/ Baltzer Mobile Networking and Applications (MONET)*, special issue on "Mobile and Pervasive Commerce", 2004, (6), 663-677.
- [19] Demetriou, A., Efklides, A. and Platsidou, M. The architecture and dynamics of developing mind: Experiential structuralism as a frame for unifying cognitive development theories. *Monographs of the Society for Research in Child Development*, 1993, 58 (Serial No. 234), 5-6.
- [20] Demetriou, A. and Kazi, S. Unity and modularity in the mind and the self: Studies on the relationships between self-awareness, personality, and intellectual development from childhood to adolescence. London: Routledge, 2001.
- [21] Witkin H., Moore C., Gooddenough D., Cox P., «Field- dependent and field- independent cognitive styles and their educational implications», *Review of Educational Research* 47, 1977, σελ. 1-64.
- [22] Riding R., "Cognitive Style Analysis – Research Administration", Published by Learning and Training Technology, 2001.
- [23] Henke H., «Applying Kolb's Learning Style Inventory with Computer Based Training», 2001, sage.sdsu.edu/compswiki/uploads/CompsWiki/learntheory.pdf.
- [24] Tsianos, N., Germanakos, P., Mourlas, and Meimaris, M. The Learning Styles as a Basic Parameter for the Design of Adaptive e-Learning Environments. Proceedings of the 3rd International Conference on Open and Distance Learning: 'Applications of Pedagogy and Technology' (ICODL2005), Patras, November 11-13, 2005, pp 651-668.
- [25] Felder M.R., and Soloman A.B. Learning Styles and Strategies, [on-line], <http://www.ncsu.edu/felder-public/ILSdir/styles.htm>.
- [26] Felder R., Spurlin J., "Application, reliability and validity of the Index of Learning Styles", *Int. J. Engng Ed.* Vol. 21, No. 1, pp 103-112, 2005.