Chapter IX
Individual Differences in Adaptive Educational Hypermedia:
The Effect of Cognitive Style and Visual Working Memory

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ABSTRACT

The purpose of this chapter is to experimentally explore the effect of individual differences in an adaptive educational hypermedia application. To that direction, the constructs of cognitive style (Cognitive Style Analysis) and visual working memory (visuo-spatial subsystem of Baddeley's model) were employed as personalization parameters, thus rendering possible the provision of personalized learning environments according to users' intrinsic characteristics. Two distinct experiments were conducted, with a total sample of 347 university students, seeking out to ground the hypothesis that matching the instructional style to learners' preferences would increase their performance. Both experiments demonstrated that users in the personalized condition generally outperformed those that were instructed in a condition mismatched to their cognitive style or visual working memory ability.

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INTRODUCTION

Web-based educational applications have proliferated throughout the extensive development of the internet, in parallel with a significant research interest on this channel of instruction. Individual differences in e-learning constitute an interdisciplinary research area, and most approaches derive from the fields of Computer Science and/or Psychology, as a result of combined efforts to improve the effectiveness of web-based education.

In any case, it is a fact that web information resources are numerous, and the internet has become extremely vague (De Bra, Aroyo & Chepegin, 2004), making information processing very difficult for users. This has provided a good basis for the notion of personalization and for the development of adaptive hypermedia systems (Eklund & Sinclair, 2000; Brusilovsky & Nejdl, 2004;), that take into account users' (or learners') individual characteristics, aiming to provide tailor-suited information.

The integration of human factors or traits in web-based education is also under the scope of many researchers, and in accordance to the aims of this paper we consider that this research is being carried out in two distinct ways: (a) computer scientists have developed systems that usually adapt on users' learning or cognitive styles (Papanikolaou et al, 2002; Carver, Howard & Lane, 1999; Gilbert & Han, 2002) or respond to their current affective state (Picard, 1997), whereas (b) researchers mainly from the field of Psychology have examined the role of different cognitive traits in computer-mediated learning (De Stefano & Lefevre, 2007; Graff, 2003; Graff 2005, Bilda, 2007; Parkinson & Redmond, 2002; Federico, 2000; Workman, 2004). It is evident that the constructs of learning and cognitive styles have proven to be quite popular in this area, whilst the concept of the Working Memory (WM) has also gained some popularity in terms of examining interaction of WM span with different hypertext levels of complexity (De Stefano, 2007; Lee & Tender, 2003). Moreover, there have been efforts to build more complex models of human factors that may be proven useful in e-learning applications (Germanakos et al, 2007a; Lin, Kinshuk & Patel, 2003).

The main idea behind these approaches is to improve the effectiveness of web-based instruction by not ignoring individuals' top-down processes (Eysenck & Keane, 2005), and to determine which factors (mainly cognitive) have a dominant role in web-based information processing. These efforts could be characterized as the first steps of introducing the notion of individual differences into web-based education, even if there are severe limitations imposed by the structure of the web.

On the basis of the aforementioned research directions in e-learning, we are in the process of developing and evaluating both a theoretical model of information processing in the web (Germanakos et al, 2007a), and a corresponding Adaptive Hypermedia system that implements our theoretical approach and assumptions (Germanakos et al, 2007b). Our experimental model is comprised of three dimensions: Cognitive Style, Cognitive Processing Efficiency and Emotional Processing. The first dimension is unitary, whereas Cognitive Processing Efficiency is comprised of (a) Working Memory Span (WMS) (Baddeley, 1992) and (b) speed and control of information processing (Demetriou, 1993). The emotional aspect of the model focuses on different aspects of anxiety (Cassady & Johnson, 2002; Cassady, 2004; Spielberger, 1983) and self-regulation.

Existing hypermedia systems mostly focus on a single cognitive construct, usually learning style, and both evaluation and assessment of the system in terms of benefit for the learners are often neglected or methodologically less elaborated. In our research we make efforts to theoretically introduce new concepts into web-based education and to experimentally assess the value of the proposed human factors. This process is continuous and revisions of the theoretical framework are

driven by experimental results. In that sense, we differentiate our system from previous rather rigorous and not extensively evaluated system realizations.

Whilst the experiments we have conducted were focused consecutively on all three dimensions, we consider that the first level of evaluating our approach would be the assessment of the personalizing process on the basis of cognitive style and working memory. These two factors are somehow more supported in literature, in the sense that hypermedia design implications and guidelines are more easily extracted from the theoretical framework.

It should be mentioned though that building a web-based system that can automatically adapt the educational content to learners' preferences or abilities is a difficult and challenging problem. It requires an automated mechanism that is not possible to include all aspects of a cognitive psychological theory; the web structure can be altered but not without limitations, web objects are of a specific form (pre-determined images, text, video and audio), and the "intelligent" functions of an application are in fact rule-based. Therefore, while a tutor in a traditional classroom can interpret and apply a theory in a flexible and intuitive way, in the case of an online educational system designers have to experimentally conclude to an implementation suitable for most learners.

This paper addresses two main issues respectively: (a) to examine how can a web-based system incorporate cognitive traits such as cognitive style and working memory in consistence to theory that has not been grounded in the context of the web and (b) to evaluate whether personalizing an e-learning procedure on the basis of such traits can increase learners' levels of comprehension (or performance). It is clear of course that the former is a prerequisite for the latter.

The next section presents the rationale behind incorporating specific theories into our approach, with regards to the nature of the web. Section 3 presents the way our system provides personalization that is consistent to our theoretical assumptions. The experimental methodology and results/discussion are presented at sections 4 and 5 respectively, while the last section focuses on conclusions, further research considerations and limitations of the study.

THEORETICAL BACKGROUND

As mentioned above, the factors that we focused upon at this phase of our research were cognitive style and visual working memory span (VWMS). Both these constructs are related to information processing, and the actual effect of these parameters in the context of the web is yet to be elucidated. As it will be discussed later, what is more important is the interaction of these two parameters that has yielded interesting results.

Cognitive Style

Cognitive style has been defined by Messick as consistent individual differences in preferred ways of organizing and processing information and experience, a construct that is different than learning style (Sadler-Smith, 2001). Cognitive styles represent an individual's typical or habitual mode of problem solving, thinking, perceiving or remembering, and "are considered to be trait-like, relatively stable characteristics of individuals, whereas learning strategies are more state-driven…" (McKay, Fischler & Dunn, 2003). The use of cognitive style has also been supported by Sternberg and Grigorenko (1997) as "…an important interface at the border of personality and cognition".

According to Curry's onion model (Curry, 1983), cognitive style theories fall into the innermost layer of "cognitive personality style", which is the most stable and relatively permanent; the factor of stability is quite important in user profiling considerations that will be discussed later.

A study by Lee et al (2005) suggests that style is essential in order to accommodate for different user needs. Indeed, this idea has been explored in systems such as the INSPIRE (Papanikolaou et al, 2003), CS383 (Carver, Howard & Lane, 1999), Arthur (Gilbert & Han, 2002) and AES-CS (Triantafillou, Pomportsis and Demetriadis, 2003) to name a few.

Amongst an impressive number of cognitive and learning style theories (Cassidy, 2004; Rayner & Riding, 97), we have used the concept of cognitive rather than learning style for a number of reasons:

- Cognitive style is not restricted to the context of strictly educational settings, since the focus is on information processing in general. This seems to be better aligned with the generic structure of the web, where learning can be widely differentiated from traditional classroom environments and strategies.
- Learning styles are "a construct that by definition is not stable- it was grounded in process and therefore susceptible to rapid change" (Rayner, 01).
- Most learning style theories, such as Kolb's (2005), Honey and Mumford's (1986) or Dunn's (1989), have a social dimension in the proposed typologies; some types are more socially oriented in learning than others. However, web-based education is often an individual process, usually asynchronous. Therefore, since we are also interested in building a generic model of information processing in the web, this family of typologies includes parameters that are not found in web-based environments.

More specifically, Riding and Cheema's Cognitive Style Analysis (CSA) has been used for quite relevant reasons. The CSA is actually derived from a factor analytic approach on previous cognitive style theories, summarizing a number of different yet highly correlated constructs into two distinct independent dimensions (Riding and Cheema, 1991). This covers a wide array of the former cognition based style typologies, without going into unnecessary depth- for the needs of web education that is.

Most importantly, the two independent scales of the CSA (verbal/imager and wholist/analyst) correspond ideally to the structure of web environments. A personalized environment that is supported by an automated mechanism can be altered mainly at the levels of content selection and hypermedia structure; the content is essentially either visual or verbal (or auditory), while the manipulation of links can lead to a more analytic and segmented structure, or to a more holistic and cohesive environment. These are actually the differences in the preferences of learners that belong to each dimension of the CSA scales (Sadler-Smith & Riding, 1999).

Subsequently, the mapping of personalized educational material on learners' preferences (or profiles) can take an actual form of well defined rules and it does not rely on heavily hypothesizing or is susceptible to designers' subjective reasoning (e.g. what is considered to fit better an accommodator or an assimilator according to Kolb's theory?).

An interesting point of view over the physiological basis of cognitive style and the use of the CSA as a psychometric tool of classification is the correlation with hemispherical preference and EEG measurements that has been reported (Glass & Riding, 1997; McKay, Fischler & Dunn, 2003). This seems to strengthen the relationship between cognitive style and actual mode of information processing.

Finally, the CSA has been also applied in other multimedia applications with significant results (Ghinea & Chen, 2003), while the test has been developed electronically; therefore we didn't have to worry about how to construct an electronic version of a psychometric tool.

At this point we must clarify that we are not unaware of reports that question the reliability of the CSA (Rezai & Katz, 2004; Peterson, Deary & Austin, 2003). The assessment of style is still an issue, and definitely practical reasons such as the ones described above should not become the sole criterion of adopting a theory. However, judging from our results that will be presented later, research-wise the CSA has been shown to support its underlying theoretical basis, at least within the boundaries of a web-based environment.

Conclusively, our rationale behind using the construct of cognitive style as a personalization factor in educational hypermedia is to provide learning environments that are matched to learners' preferences, in order to increase their level of comprehension and performance. Consequently, our research hypothesis is that those who are taught in the supposedly ideal condition of matched teaching and learning style will outperform other learners.

Working Memory

The concept of working memory (Baddeley, 1981) also fits very well into our rationale of personalizing the educational web-content on the basis of learners' cognitive abilities and preferences. "The term working memory refers to a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" (Baddeley, 1992); Baddeley also refers to individual differences in the working memory (digit) span of the population, thus providing a very good argument for using this concept as a personalization factor.

A brief description of the working memory system is that is consisted of the central executive that controls the two slave systems (visuo-spatial sketchpad and phonological loop), plus the episodic buffer that provides a temporary interface between the slave systems and the Long Term Memory (Baddeley, 2000). We are mainly interested in the notion of the working memory span, since it can be measured and the implications on information processing are rather clear. Due to the visual form of presentation in the web, we have focused especially on the measurement of visual working memory (Logie, Zucco & Baddeley, 1990) in terms of psychometrics- this will be discussed further in the methodology section.

The idea of exploring the role of working memory in hypertext environments has indeed generated research. DeStefano and LeFevre (2007) reviewed 38 studies that address mainly the issue of cognitive load in hypertext reading, and working memory is often considered as an individual factor of significant importance, even at the level of explaining differences in performance. Lee and Tedder (2003) examine the role of working memory in different computer texts, and their results show that low working memory span learners do not perform equally well in hypertext environments. The term Cognitive Load Theory is often used when referring to guidelines for designing hypermedia applications, and it is often correlated with working memory span (Kirchsner, 2002).

As depicted in the previous section, the role of working memory will not been examined separately, but in parallel with cognitive style. Our proposed web-based environment provides personalization on the basis of both these two parameters, and their combined effect is expected to support the argument for personalization on cognitive traits. This somehow differentiates our approach from the ones mentioned above, in the sense that in our case the hypermedia structure is mainly affected by cognitive style rather than working memory span, while the latter concept affects the amount of information provided (as to decrease cognitive load).

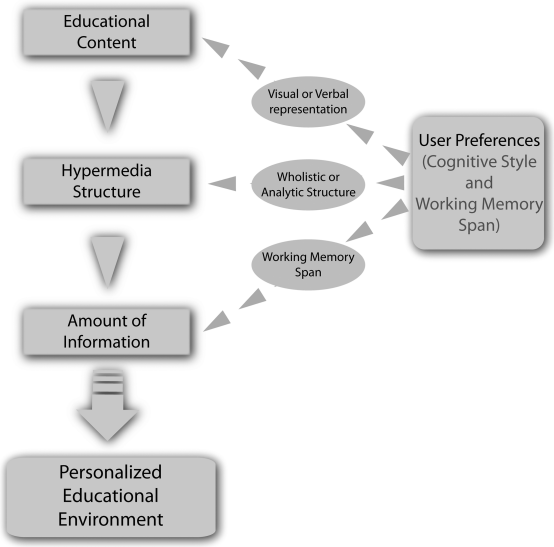
The interaction of working memory and cognitive style has also been explored by Riding, Grimley, Dahrai and Banner (2003). In sum, their results show that in a traditional classroom setting analytics and verbalizers are more susceptible to

working memory span deficiencies, since both these methods of processing information are more demanding in resources. Though this is probably true, our rationale is to alleviate such differences in performance by personalizing the online educational environment to each learner's preferences.

Therefore, the approach we describe in this paper leads to an educational adaptive hypermedia architecture that may be separated into subsequent phases (Figure 1).

Firstly, according to learner's visual or verbal preference, the appropriate content is selected; this of course requires adequate learning objects or resources (both visual and verbal), but it's rather a technical than a theoretical issue. Next, the structure of the environment is built upon learner's way of organizing information (holistically or analytically). This includes the organization of links, the navigational tools and the amount of learner control (framed/holistic or free/analytic navigation). Finally, the segmentation of simultaneously presented information is affected by individual's visual memory digit span. The aggregation of the aforementioned personalization factors leads to a personalized educational environment. The whole process is supported by existing Information Technologies (IT).

Figure 1. Personalization architecture



The theoretical approach we have described has necessary lead us to the following research questions:

- Is it possible to map learners' cognitive style and working memory span on an adaptive educational environment in a coherent and meaningful way?
- Are these parameters actually important in the context of web-based education, in terms of increasing comprehension and performance?

Before presenting the methodology and the results of the experiment we have conducted, we should briefly describe how our system maps learners' cognitive preferences on the information space.

THE ADAPTIVE WEB INTERFACE

The reasons for this brief description of the educational platform that has been used to conduct our experiments are: (a) to illustrate an instructional approach that in our opinion "translates" the cognitive theories that we have adopted into web-design implications and (b) to provide the reader with a more specific and comprehensive insight of the overall methodology we have used.

At the level of e-learning instruction, we should point that the issue of general approved design guidelines is not yet resolved, and we consider that this happens also with the use of learning/cognitive styles by previous efforts in adaptive hypermedia systems. The working memory span implications, on the other hand, seem to be better elaborated.

The system and a "guided" tour can be accessed in the following url: http://www3.cs.ucy.ac.cy/ adaptiveweb/.

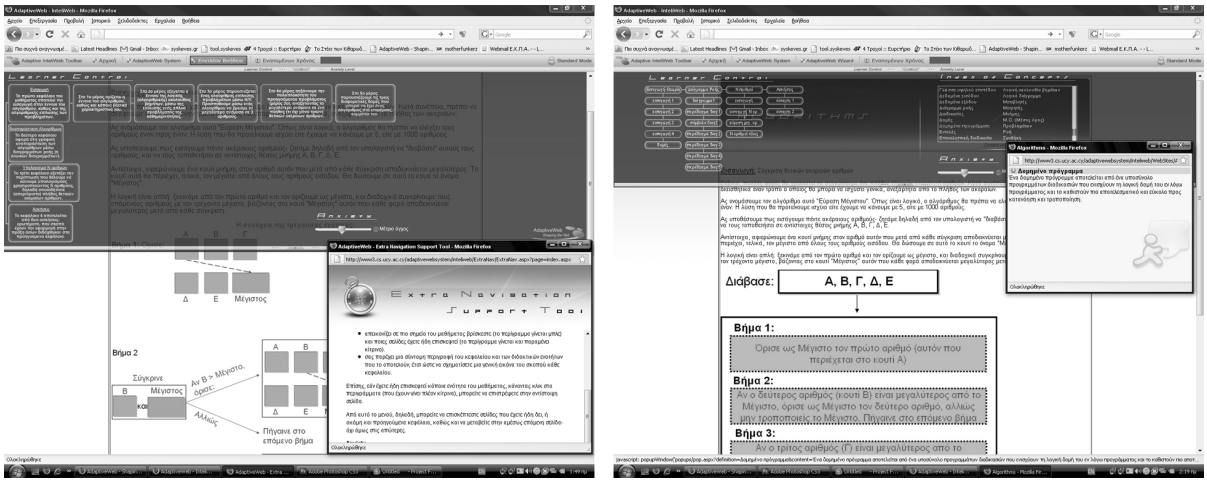
Nevertheless, in our system these cognitive factors are translated in a coherent way into actual learning personalization parameters, remaining as consistent as possible to the theories described in the previous section (Riding, 91; Baddeley, 1992), as follows:

- **Imager (cognitive style):** Images, diagrams and schemes are used, when possible, for the representation of information. Specifically, instead of lengthy verbal descriptions, a schematic approach has been adopted as an equally important mean of instruction. Text is also used, but is reduced by app. 40% in comparison to verbal learners.
- **Verbal (cognitive style):** The prominent representation of information is textual, and images are used when required, accompanying and not replacing texts.
- **Analyst (cognitive style):** In the analytic condition, learners are free to navigate through the educational environment. They are not guided externally, though they may choose to follow a linear suggested path. They also have access to a separate index of concepts in order to follow an analytic path in accessing information and forming knowledge. The information is extensively interconnected since hypertext is used at a greater extent, and users can access at the same time different parts of the educational content.
- **Wholist (cognitive style):** In the wholist condition learners navigate through the environment in an externally guided way, which provides prefixed linkage and descriptions of the sequentially interconnected information. The organization of the distinct parts of the course is strict and outlined in a clear way. Users have access to previously acquired information, but they do not have access to links that lead to information of chapters not visited. Additional guiding information is constantly given.

Figure 2 illustrates the differences between the imager/wholist and the verbal/analytic version of the same webpage:

- **Intermediate (cognitive style):** Intermediate users are provided with an environment which combines characteristics of all dimensions of cognitive style, in order to maintain a balance; moreover, they serve as a control group in our experiments.

Figure 2. An imager/wholist (left) and a verbal analytic environment (right)



- **Low Visual Working Memory Span:** Since a large amount of information, especially when presented in the form of hypertext, may impair learners' comprehension, the system presents web-objects in a consecutive way, allowing users to devote more reading time to each resource. Learning objects do not disappear when the next ones are provided; on the contrary, each lesson "unfolds" gradually.
- **Medium/High Visual Working Memory Span:** Users with medium and high WMS are treated the same, since we are interested in alleviating difficulties and not boosting efficient learners.

It is evident that the instructional value of such an approach can be evaluated only experimentally, in the absence of well defined grounded guidelines for the purposes of web-based education.

METHOD

Our results were gathered from two subsequent experiments. In both cases, the experimental design was a between participants memory posttest, in order to assess the differences in performance between learners who were taught in a personalized, matched to their preferences way, and those who were taught in a way that was not consistent to their cognitive preferences. Those that were classified as intermediates (no cognitive style preference) received a non-personalized balanced environment.

The three conditions (matched, mismatched and "intermediate" way of teaching) were expected to provide statistically significantly different results only if the factors involved are indeed important for web-based learning.

The first experiment was conducted at the University of Cyprus, while the second was conducted at the University of Athens. The aim of the first experiment was to clarify whether matching (or mismatching) instructional style to users' cognitive style improves performance. The second experiment focused on the importance of matching instructional style to VWMS.

Sample and Procedure

All participants were students from the Universities of Cyprus and Athens; experiment I was conducted with a sample of 138 students, whilst experiment II with 209 individuals. Approximately 30% of the participants were male and 70% were female, and their age varied from 17 to 22 with a mean age of 19. Participating in the experiment was voluntary, though most students were willing to take the course, as an additional help on a difficult academic subject that is part of their academic curriculum. We should clarify that there was not any pretesting, or restrictions to participation, other than lack of previous knowledge. Both experiments were conducted in July of 2007.

The environment in which the procedure took place was an e-learning introductory course on algorithms. The specific subject was chosen due to the fact that students of the social sciences departments where the experiment took place had absolutely no experience of programming and computer science and traditionally perform poorly. By controlling the factor of experience in that way, we divided our sample in two groups: almost half of the participants were provided with information matched to their cognitive preferences, while the other half were taught in a mismatched way. We expected that users in the matched condition, both in experiments I and II, would outperform those in the mismatched condition. The two groups were divided randomly, in the sense that each user that logged into the system received the opposite to the previous user condition.

In order to evaluate the effect of matched and mismatched conditions, participants took an online memory test on the subject they were taught (algorithms). This exam was taken as

soon as the e-learning procedure ended, in order to control for long-term memory decay effects. The dependent variable that was used to assess the effect of adaptation to users' preferences was participants' score at the posttest.

Learners accessed the environment through a web browser, using personal computers located at the laboratories of both universities. Participants took the tests and built their profiles before participating at the online course. Users' profiles were kept at the system database. The assignment of participants in the matched or mismatched condition was quasi random- the first user that logged in received a matched environment, the second a mismatched, and the condition was consecutively alternated. The system provided a matched or mismatched environment for each user by accessing his/her profile from the database. The actualization of each environment was based on a simple algorithm; according to each user characteristic, a visible aspect of the environment was personalized on the basis of the aforementioned rules presented in section 3.

The profiling procedure lasted for about 20 minutes; after that, users' were encouraged to take a 5-10 min break. The course lasted for approximately 40 minutes, and the memory test for about 15 minutes.

Materials

In this specific e-learning setting, cognitive style and VWMS were the main parameters consisting each user profile, since demographics and traditional profiling characteristics were controlled for by the homogeneity of the sample (although we also gathered information concerning these parameters).

The tools we used were:

- **Cognitive Style:** Riding's Cognitive Style Analysis, standardized in Greek and implemented in the .NET platform. The test is separated in three parts: the first part assesses the imager/verbalizer dimension by calculating the time required for participants to construct mental representations of 24 given sentences. In the following two phases, the time that users devote to integrate or disambiguate two sets of figures indicates their position on the analyst/wholist axis. The latter phases are based on Witkin's et al Group Embedded Figures Test (1971).
- **Visual Working Memory Span:** Visuospatial working memory test (Demetriou, A., Christou, C., Spanoudis, G., & Platsidou, M., 2002), firstly developed at the E-prime platform, afterwards implemented in the .NET platform. This visual memory test examines participants' ability to temporarily store visual figures. Each figure that has to be remembered is shown for two seconds, and afterwards a set of five figures is presented, including the one that had to be stored. Users are asked to identify the figure that was shown before. Complexity and resemblance of the stimuli increases gradually. There are a total of 21 figures, divided in three broad categories: low VWMS learners should to be able to answer the first group of seven, medium VWMS learners are expected to progress to the next seven, while the remaining seven require high visual working memory span.

The reasons we used the CSA were presented at the theoretical framework section of the paper. Regarding the use of the specific working memory span measurement tool, we adopted the specific approach because it can be easily presented visually in a computer screen, and most importantly all information presented in the experimental procedure is actually visual and not auditory; therefore we considered that measuring this aspect of the working memory span can provide an adequate indication of learners' WM span in the web environment.

The e-learning course, the profiling building procedure and the psychometric tools can be accessed at http://www3.cs.ucy.ac.cy/adaptiveweb/.

RESULTS AND DISCUSSION

Experiment I

As hypothesized, the mean score of those that received matched to their cognitive style environments is higher than the mean score achieved by those that learned within the mismatched condition (see table 1). Since the variance of participants' scores was homogeneous (Levene's statistic=0.20, p=0.980) one way analysis of variance was performed on the data. The difference in score between the three groups (matched, mismatched and intermediates) is statistically significant: $F_{(2,137)}=3.479$, p=0.034 (see table 2).

Post hoc analysis has shown that the difference is significant only between groups in the matched and the mismatched condition (8.741 percentage points in the memory posttest), whilst intermediates do not differ from any of the other two categories (see table 3).

As depicted in the theoretical framework section, intermediate users have no specific cognitive style preference. Consequently, they received a non-personalized (though balanced) environment; this may explain the fact that their mean score does not differ significantly from those that learned in the matched condition, since any environment could be proven as matched for them.

Still, the fact that their score also does not differ from the mismatched condition participants', could perhaps be attributed to some other variable that may be of significant importance in performance, as long as there are not cognitive style preferences to be satisfied.

We should note that a closer inspection of the means for all categories of learners placed in both axes of cognitive style (Imager/Intermediate/Verbalizer and Wholist/Intermediate/Analyst) shows that the differences in score are often very high

Table 1. Descriptives of differences in mean score of matched and mismatched condition Score %

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Matched	53	66.53	18.901	2.596	61.32	71.74	13	100
Mismatched	61	57.79	18.149	2.324	53.14	62.44	9	93
Intermediate	24	58.58	18.429	3.762	50.80	66.37	22	93
Total	138	61.28	18.821	1.602	58.11	64.45	9	100

Table 2. ANOVA for differences in mean score of matched and mismatched condition Score %

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2378.708	2	1189.354	3.479	**.034**
Within Groups	46153.270	135	341.876		
Total	48531.978	137			

between the two conditions, with the exception of the Verbalizer-Wholist learners, who do not seem to benefit from the personalization of the web-content. This can be explained by the fact that the specific cognitive style preference is considered to be complementary (Riding & Wigley, 1997) and more adaptive to mismatched situations.

Though learners' VWMS was not a factor of personalization in this experiment, this measurement was also available. This independent variable had no effect of its own, nor interaction with each experimental condition (matched/ mismatched/ intermediate environment) on participants' scores. Also, in the mismatched and intermediate condition, VWMS is insignificant.

However, in the matched condition VWMS becomes significant, since a 3X3 ANOVA has shown interaction between WMS and the Wholist/Analytic dimension on participants' scores ($F_{(4,52)}$=3.506, p=0.014) . According to theory, analysts are in further need of working memory span in order to use their analytic mode of processing; thus, analysts with low working memory span should perform worse- which is the case with this experiment. Besides that, wholists also benefit from high levels of VWMS (though not from medium levels), whilst intermediates demonstrate a rather reverse behaviour (see table 4). This latter finding is somehow puzzling, and it should be further experimentally investigated.

Table 3. Post hoc analysis of differences in mean scores
Dependent Variable: Score %
Tukey HSD

(I) Matched Environment	(J) Matched Environment	Mean Difference (I-J)	Sig.
Matched	Mismatched	8.741(*)	**.034**
	Intermediate	7.945	.192
Mismatched	Matched	-8.741(*)	**.034**
	Intermediate	-.796	.983

** The mean difference is significant at the .05 level.*

Table 4. Estimated marginal means of Wholist/Analyst dimension interaction with VWMS
Dependent Variable: Score %

				95% Confidence Interval	
Wholist/Analyst	W.M.S.	Mean	Std. Error	Lower Bound	Upper Bound
Analyst	Low	63.000	8.818	45.228	80.772
	Medium	100.000	10.800	78.234	121.766
	High	87.000	10.800	65.234	108.766
Intermediate	Low	85.500	7.637	70.109	100.891
	Medium	66.400	6.831	52.634	80.166
	High	74.833	6.235	62.267	87.400
Wholist	Low	56.917	4.409	48.031	65.803
	Medium	55.357	4.082	47.130	63.584
	High	76.400	6.831	62.634	90.166

The findings of this experiment may support the notion that applying a cognitive style theory in the context of the web could be proven useful for learners, or at least that mismatching the web-environment to their preferences may hamper their performance. The mean difference of app. 9% is not striking of course, but taking under consideration the little variance of participants' scores, it could be supported that organizing information in the web-space according to learners' preferences can provide added value to an e-learning application.

Experiment II

In this experiment, only learners with low VWMS are involved in the two conditions (match/mismatch); those with medium/high VWMS are considered as a control group that do not require any manipulation of the web-content in order to learn efficiently.

The results are quite similar to the first experiment. Segmentation of the web-content for low VWMS learners (matched condition) increases their performance, while users that receive the same with the control group content perform worse (see table 5). Since the variance of participants' scores was homogeneous (Levene's statistic=1.038, p=0.356), one way ANOVA has shown that this difference is statistically significant: $F=5.623_{(2,208)}$, p=0.004 (see table 6).

Post hoc analysis of the data has shown that mismatched (low VWMS) learners differ significantly from the control group (minus 10.086 percentage points), while matched (low VWMS) learners do not. Even so, since matched learners have scored between the two other categories, they also do not differ significantly from the mismatched learners (see table 7).

Subsequently, since cognitive style preference is controlled for, it seems that VWMS is significant in achieving higher performance. Nevertheless,

Table 5. Descriptives of differences in mean score of matched and mismatched condition Score %

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
match	42	56.10	18.404	2.840	50.36	61.83	26	93
mismatch	41	50.05	15.735	2.457	45.08	55.02	20	82
control	126	60.13	16.817	1.498	57.17	63.10	19	93
Total	209	57.34	17.317	1.198	54.98	59.71	19	93

Table 6. ANOVA for differences in mean score of matched and mismatched condition Score %

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	3228.968	2	1614.484	5.623	**.004**
Within Groups	59144.228	206	287.108		
Total	62373.196	208			

personalizing the web-content according to users' working memory span seems to moderate the negative effect of low VWMS on learning. This is actually the idea that supports the notion of personalization in adaptive web-environments: to incorporate into the system functional components that address users' needs in a way that their differences are not hampering their information processing of the web-content in an equally efficient way.

Nonetheless, it must be clearly stated that this interaction needs to be elaborated in a more complex process of personalization, by addressing more aspects of individual differences in working memory span. These results can be considered as rather indicative of the role of working memory in web-based indication, which of course is not really a novel finding, and most importantly provide a basis for investigating ways to alleviate difficulties that individual differences may impose on e-learning processes.

CONCLUSION

The notion of integrating individual differences approaches from the field of social sciences, predominantly derived from psychological research, has a great appeal to developers of information and learning multimedia/hypermedia systems. The fact that the technologies that such systems are based on often have an adaptive and/or semantic nature enhances the role and importance of individual user profiling. Since it is now possible to develop systems that adapt to each unique user, processes such as learning can be highly personalized.

Nevertheless, these technologies and the predefined at some extend structure of hypermedia/multimedia systems impose certain constraints on the individual characteristics that can be included in users' profile in order to comprise personalization factors. More specifically, in the case of e-learning, though there are many educational and pedagogical theories of undisputable value, the structure of the web limits the range of possible implementations.

Our approach focuses on matching some aspects of web-based learning to learners' corresponding characteristics, with regards to the organization, presentation and segmentation of information. Constructs such as cognitive style (especially based on the axis of field dependence/field independence) and working memory seem to address these issues at a satisfying extent.

The experiments presented in this paper also seem to validate such an approach, though not at a conclusive level, since there are limitations in our study that should be also taken into account. First of all, building web-environments that

Table 7. Post hoc analysis of differences in mean scores
Dependent Variable: Score %
Tukey HSD

(I) Matched WM	(J) Matched WM	Mean Difference (I-J)	Sig.
match	mismatch	6.046	.237
mismatch	control	-10.086(*)	**.003**
control	match	4.040	.376
	mismatch	10.086(*)	**.003**

* *The mean difference is significant at the .05 level.*

respond to learners' preferences has been a trial and error procedure, since there is no comprehensive theory of web-design with regards to these issues. The translation of theory into practice is by itself a challenge, which has been carried out in a conservative way. Experimentally, our web environment has provided us with rather clear indications, but in terms of a comprehensive learning system there is more research to be conducted. Moreover, even if the role of VWMS has been experimentally underlined, the personalization process should be more elaborated than simply segmenting the web-content, although this has been proven somehow useful.

We also did not take into account the social aspect of web-learning and the implications of collaborative learning, which are certainly of importance, but instead we have focused exclusively on individuals' processing of web-information. Perhaps in a collaborative environment these factors could interact with socializing processes in an interesting way. Finally, we used the specific psychometric tools not only because of the theories underlying them, but also for convenience reasons (suitable and optimized for the web).

Besides further experimental evaluation of the role of working memory (and not merely visual working memory span), a major part of our future work is the role of the emotional state of the user and possible interactions with the cognitive constructs that this paper addresses. We have already constructed a computer mouse that has Galvanic Skin Response and heart rate sensors integrated, and we are in the process of seeking out personalization rules for learners with high levels of academic anxiety. The utter aim is to gradually develop a comprehensive user model for educational adaptive hypermedia. Still, for the time being, experiments are conducted in the direction of an in-depth exploration of Baddeley's working memory model not only in educational but also in e-services web-environments.

Even so, in the specific context of web-learning, learners that are being taught in an environment that is personalized on the basis of their cognitive style and VWMS outperform those that do not have their preferences satisfied. The latter may be the case with non-personalized e-learning courses, where the designers' style predominates, allowing random matching or mismatching of teaching and learning style. Though we do not claim that an event like that would undoubtedly be heavily influencing learners in a negative way, there could possibly be a difference in performance, mainly attributed to such a random matching/mismatching.

Personalization, on the other hand, aims to the resolution of these issues, and in our opinion the constructs of cognitive style and working memory seem to offer an insight with regards to the ways people interact with a web-based learning environment; thus, optimization of performance may be significantly correlated with satisfying learners' preferences.

REFERENCES

Baddeley, A. (2000). The episodic buffer: A new component of working memory? *Trends in Cognitive Sciences*, *11*(4), 417-423.

Baddeley, A. (1992). Working memory. *Science*, *255*, 556-559.

Baddeley, A. (1981). The concept of working memory: A view of its current state and probable future development. *Cognition*, *10*(1-3), 17-23.

Bilda, Z., & Gero, J. S. (2007). The impact of working memory limitations on the design process during conceptualization. *Design Studies, 28*(4), 343-367.

Brusilovsky, P., & Nejd, W. (2004). Adaptive hypermedia and adaptive Web. In M. P. Singh (Ed.), *The practical handbook of Internet computing* (pp. 1.1-1.14). USA: Chapman & Hall/CRC.

Carver, C. A., Jr., Howard, R. A., & Lane, W. D. (1999). Enhancing student learning through hypermedia courseware and incorporation of student learning styles. *IEEE Transactions on Education, 42*(1), 33-38.

Cassady, J. C., & Jonhson, R. E. (2002). Cognitive test anxiety and academic performance. *Contemporary Educational Psychology*, *27*(2), 270-295.

Cassady, J. C. (2004). The influence of cognitive test anxiety across the learning–testing cycle. *Learning and Instruction*, *14*(6), 569-592.

Cassidy, S. (2004). Learning styles: An overview of theories, models, and measures. *Educational Psychology*, *24*(4), 419-444.

Curry, L. (1983). *An organization of learning styles theory and constructs.* Paper presented at the Annual Meeting of the American Educational Research Association, 67th, Montreal, Quebec.

De Bra, P., Aroyo, L., & Chepegin, V. (2004). The next big thing: Adaptive Web-based systems. *Journal of Digital Information*, *5*(1).

De Bra, P., & Calvi, L. (1998). AHA: A generic adaptive hypermedia system. In *Proceedings of the 2nd Workshop on Adaptive Hypertext and Hypermedia, HYPERTEXT'98,* Pittsburgh, USA.

Demetriou, A., Christou, C., Spanoudis, G., & Platsidou, M. (2002). The development of mental processing: Efficiency, working memory, and thinking. *Monographs of the Society for Research in Child Development, 67*(1), 1-155.

Demetriou, A., Efklides, A., & Platsidou, M. (1993). *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). Chicago, IL: University of Chicago Press.

DeStefano, D., & Lefevre, J. (2007). Cognitive load in hypertext reading: A review. *Computers in Human Behavior*, *23*(3), 1616-1641.

Dunn, R., & Dunn, K. (1989). *Learning style inventory.* Lawrence, KS: Price Systems.

Eklund, J., & Sinclair, K. (2000). An empirical appraisal of the effectiveness of adaptive interfaces of instructional systems. *Educational Technology and Society*, *3*(4), 165-177.

Eysenck, M. W., & Keane, M. T. (2005). *Cognitive psychology.* (5th ed.). New York: Psychology Press.

Federico, P. (2000). Learning styles and student attitudes toward various aspects of network-based instruction. *Computers in Human Behavior*, *16*(4), 359-379.

Germanakos, P., Tsianos, N., Lekkas, Z., Mourlas, C., & Samaras, G. (2007a). Capturing essential intrinsic user behaviour values for the design of comprehensive Web-based personalized environments. *Computers in Human Behavior (2007).* doi:10.1016/j.chb.2007.07.010

Germanakos, P., Tsianos, N., Lekkas, Z., Mourlas, C., Belk, M., & Samaras G. (2007b). An adaptive Web system for integrating human factors in personalization of Web content. In *Proceedings of the 11th International Conference on User Modeling (UM 2007)*, Corfu, Greece.

Ghinea, G., & Chen, S. Y. (2003). The impact of cognitive styles on perceptual distributed multimedia quality. *British Journal of Educational Technology, 34*(4), 393-406.

Gilbert, J. E., & Han, C. Y. (2002). Arthur: A personalized instructional system. *Journal of Computing in Higher Education, 14*(1), 113-129.

Glass, A., & Riding, R. J. (1999). EEG differences and cognitive style. *Biological Psychology*, *51*(1), 23-41.

Graff, M. G. (2003). Learning from Web-based instructional systems and cognitive style. *British Journal of Educational Technology*, *34*(4), 407-418.

Graff, M. G. (2005). Differences in concept mapping, hypertext architecture, and the analyst–intuition dimension of cognitive style. *Educational Psychology*, *25*(4), 409-422.

Honey, P., & Mumford, A. (1986). *A manual of learning styles.* Maidenhead, UK: Peter Honey Publications.

Kirschner, P. A. (2002). Cognitive load theory: Implications of cognitive load theory on the design of learning. *Learning and Instruction*, *12*(1), 1-10.

Kolb, A. Y., & Kolb, D. A. (2005). *The Kolb learning style inventory – version 3.1 2005 technical specifications.* Boston, MA: Haygroup Experience Based Learning Systems Inc.

Lee, C. H. M., Cheng, Y. W., Rai, S., & Depickere, A. (2005). What affect student cognitive style in the development of hypermedia learning system. *Computers & Education, 45*(2005), 1-19.

Lee, M. J., & Tedder, M. C. (2003). The effects of three different computer texts on readers' recall: Based on working memory capacity. *Computers in Human Behavior*, *19*(6), 767-783.

Lin, T., Kinshuk, & Patel, A. (2003). Cognitive trait model for persistent student modelling. In D. Lassner & C. McNaught (Eds.), *EdMedia 2003 Conference Proceedings*, Norfolk, USA.

Loggie, R. H., Zucco, G. N., & Baddeley, A. D. (1990). Interference with visual short-term memory. *Acta Psychologica*, *75*(1), 55-74.

McKay, M. T., Fischler, I., & Dunn, B. R. (2003). Cognitive style and recall of text: An EEG analysis. *Learning and Individual Differences*, *14*(1), 1-21.

Papanikolaou, K. A., Grigoriadou, M., Kornilakis, H., & Magoulas, G. D. (2003). Personalizing the interaction in a Web-based educational hypermedia system: The case of INSPIRE. *User-Modelling and User-Adapted Interaction*, *13*(3), 213-267.

Parkinson, A., & Redmond, J. A. (2002). Do cognitive styles affect learning performance in different computer media? In *Proceedings of the Annual Joint Conference Integrating Technology into Computer Science Education, Proceedings of the 7th annual conference on Innovation and technology in computer science education*, Aarhus, Denmark (pp. 39-43).

Peterson, E. R., Deary, I. J., & Austin, E. J. (2003). The reliability of Riding's cognitive style analysis test. *Personality and Individual Differences*, *34*(5), 881-891.

Picard, R. W. (1997). *Affective computing.* Cambridge, MA: MIT Press.

Rayner, S. (2001). Cognitive styles and learning styles. In N. J. Smelser & P. B. Baltes (Eds.), *International encyclopedia of social & behavioral Sciences.* UK: Elsevier Science Ltd.

Rayner, S. & Riding, R. (1997). Towards a categorisation of cognitive styles and learning styles. *Educational Psychology*, *17*(1/2), 5-27.

Rezaei, A. R., & Katz, R. (2004). Evaluation of the reliability and validity of the cognitive styles analysis. *Personality and Individual Differences*, *36*(6), 1317-1327.

Riding, R. J., Grimley, M., Dahraei, H., & Banner, G. (2003). Cognitive style, working memory and learning behaviour and attainment in school subjects. *British Journal of Educational Psychology*, *73*(2), 149-169.

Riding, R. J., & Cheema, I. (1991). Cognitive styles – an overview and integration. *Educational Psychology*, *11*(3/4), 193-215.

Riding, R. J., & Wigley, S., (1997). The relationship between cognitive style and personality in further education students. *Personality and Individual Differences*, *23*(3), 379-389.

Sadler-Smith, E. (2001). The relationship between learning style and cognitive style. *Personality and Individual Differences*, *30*(4), 609-616.

Sadler-Smith, E., & Riding, R. J. (1999). Cognitive style and instructional preferences. *Instructional Science*, *27*(5), 355-371.

Spielberger, C. D. (1983). *Manual for the state-trait anxiety inventory (STAI).* Palo Alto, CA: Consulting Psychologists Press.

Sternberg, R. J., & Grigorenko, E. L. (1997). Are cognitive styles still in style? *American Psychologist*, *52*(7), 700-712.

Triantafillou, E., Pomportsis, A., & Demetriadis, S. (2003). The design and the formative evaluation of an adaptive educational system based on cognitive styles. *Computers & Education, 41*(2003), 87-103.

Witkin, H. A., Oltman, P. K., Raskin, E., & Karp, S. A. (1971). *Group embedded figures test manual.* Palo Alto, CA: Consulting Psychology Press.

Workman, M. (2004). Performance and perceived effectiveness in computer-based and computer-aided education: Do cognitive styles make a difference? *Computers in Human Behavior, 20*(4), 517-534.