Capturing Essential Intrinsic User Behaviour Values for the Design of Comprehensive Web-based Personalized Environments

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Abstract.

Advances in Web-based oriented technologies and services are taking place with a considerable speed around the world. As communications and IT usage become an integral part of many people's lives and the available products and services become more varied and sophisticated, users expect to be able to personalize a service to meet their individual needs and preferences. Due to the heterogeneous users' needs and requirements, user modeling could be considered as a successful step towards the identification of users' preferences. However, could user profiling nowadays be considered complete enough? Are all the vital parameters of users' characteristics are taken into account in order for the Web-based systems to provide them with the most user-centric result? This paper introduces a comprehensive user profiling, incorporating the User Perceptual Preference Characteristics, that serves as the core element for filtering Web-based raw content. It further analyzes the main intrinsic users' characteristics like visual, cognitive, and emotional processing parameters as well as the "traditional" user profiling characteristics that together tend to give the most optimized, *adapted and personalized result. It finally presents initial experimental results applied on the Educational field based on the abovementioned notions.*

Keywords: Adaptation, Personalization, User Profiling, Cognitive Learning Styles, Visual Attention, Emotionality

1 Introduction

The explosive growth in the size and use of the World Wide Web as well as the complicated nature of most Web structures may lead in orientation difficulties, as users often lose sight of the goal of their inquiry, look for stimulating rather than informative material, or even use the navigational features unwisely. To alleviate such navigational difficulties, researchers have put huge amounts of effort to identify the peculiarities of each user group and design methodologies and systems that could deliver an adapted and personalized web-content.

Challenges therefore range not only on adapting to the heterogeneous user needs and user environment issues such as current location and time [Panayiotou & Samaras, 2004], but also on a number of other considerations with respect to multi-channel delivery of the applications concerning Web-based content related to services, educational multimedia, entertainment, commerce etc. To this end, personalization techniques exploit Artificial Intelligence, agent-based, and real-time paradigms to give presentation and navigation solutions to the growing user demands and preferences. To this date, there has not been a concrete definition of personalization. However, many solutions offering personalisation features meet an abstract common goal: to provide users with what they want or need without expecting them to ask for it explicitly [Mulvenna et al., 2000]. In addition, a complete definition of personalization should include parameters and contexts such as user intellectuality, mental capabilities, socio-psychological factors, emotional states and attention grapping strategies, since these could affect the apt collection of users' customization requirements, offering in return the best adaptive environments to the user preferences and demands.

This paper emphasizes on the adaptation of Web-based content delivery, investigating adaptation and personalization considerations with regards to new user requirements and demands. It analyzes the significance and peculiarities of the user profiling for providing a personalized Web-based result, introducing a comprehensive user profiling that incorporates intrinsic user characteristics such as user perceptual preferences (visual, cognitive and emotional processing parameters), on top of the "traditional" ones (such as name, age, education etc.). Lastly, it presents results of experiments taken place at the Laboratory of New Technologies of the University of Athens with regards to Web-based educational content delivery based on specific cognitive styles.

2 Comprehensive User Requirements and the Personalization Problem

"To struggle against the amplification of the digital divide and therefore to think 'user interaction' whatever the age, income, education, experience, and the social condition of the citizen" [Europe's Information Society, 2004].

The specific theme above reveals exactly the need for user centered content delivery in a personalized and adaptive manner. In many ways, the new technology provides greater opportunities for access. However, there are important problems in determining precisely what users want and need, and how to provide Web-based content in a user-friendly and effective way. User needs are always conditioned by what they already get, or imagine they can get.

Additionally, it is clearly understood now that the World Wide Web introduces a new model of communication that differs from traditional media, since information is distributed in a variety of ways that enhances the proliferation of human networks [Mason & Hacker, 2003], regardless of their social, educational, economic or political orientation. This exact proliferation of innumerous human networks has resulted in a massive flow of information that burdens users' effort to seek out useful or appropriate resources [De Bra, Aroyo, Chepegin, 2004].

If we place, for example, the scope of our argument into learning, it is possible to imagine a vague network of interacting users', on both ends of the learning process, exchanging huge amounts of information, that couldn't sometimes be proven suited for every single user (especially when cognitive and learning parameters are involved). By introducing a filter of personalization, one can limit the vagueness of non-relevant information and gain easier access to resources that respond to each learner's needs. Not all people learn or process information the same way, and this vast differentiation should be taken into consideration when people form networks that deal with such processes.

The user population is not homogeneous, nor should be treated as such. To be able to deliver quality knowledge, systems should be tailored to the needs of individual users providing them personalized and adapted information based on their perceptions, reactions, and demands. Therefore, a serious analysis of user requirements has to be undertaken, documented and examined, taking into consideration their multi-application to the various delivery channels and devices. Some of the user requirements and arguments anticipated could be clearly distinguished into [CAP Gemini Ernst & Young, 2004]: (a) General User Service Requirements (flexibility: anyhow, anytime, anywhere; accessibility; quality; and security), and (b) Requirements for a Friendly and Effective User Interaction (information acquisition; system controllability; navigation; versatility; errors handling; and personalization).

Although one-to-one Web-based content provision may be a functionality of the distant future, user segmentation is a very valuable step in the right direction. User segmentation means that the user population is subdivided, into more or less homogeneous, mutually exclusive subsets of users who share common user profile characteristics enabling the possibility of providing them a more personalized content. The subdivisions could be based on: Demographic characteristics (i.e. age, gender, urban or rural based, region); socio-economic characteristics (i.e. income, class, sector, channel access); psychographic characteristics (i.e. life style, values, sensitivity to new trends); individual physical and psychological characteristics (i.e. disabilities, attitude, loyalty).

The science behind personalization has undergone tremendous changes in recent years while the basic goal of personalization systems was kept the same, to provide users with what they want or need without requiring them to ask for it explicitly. Personalization is the provision of tailored products, multimedia-based services, Web-based educational content, information or information relating to products or services. Since it is a multi-dimensional and complicated area (covering also, recommendation systems, customization, adaptive Web sites, Artificial Intelligence) a universal definition that would cover all its theoretical areas has not been given so far. Nevertheless, most of the definitions that have been given to personalization [Kim, 2000; Wang & Lin, 2002] are converging to the objective of delivering to a group of individuals relevant information that is retrieved, transformed, and / or deduced from information sources.

Moreover, the issue of personalization is a complex one with many aspects and viewpoints that need to be analyzed and resolved. Some of these issues become even more complicated once viewed from a mobile user's perspective, in other words when constraints of mobile channels and devices are involved. Such issues include, but are not limited to: What content to present to the user, how to show the content to the user, how to ensure the user's privacy, how to create a global personalization scheme. As clearly viewed, user characteristics and needs, determining user segmentation and thus provision of the adjustable information delivery, differ according to the circumstances and they change over time [Panayiotou & Samaras, 2004].

There are many approaches to address these issues of personalization but usually, each one is focused upon a specific area, i.e. whether this is profile creation, machine learning and pattern matching, data and Web mining or personalized navigation.

3 Completing "Traditional" User Profiling with the Use of Intrinsic User Values

One of the key technical issues in developing personalization applications is the problem of how to construct accurate and comprehensive profiles of individual users and how these can be used to identify a user and describe the user behaviour, especially if they are moving [Adomavicious & Tuzhilin, 1999]. According to Merriam- Webster dictionary the term profile means "a representation of something in outline". User profile can be thought of as being a set of data representing the significant features of the user. Its objective is the creation of an information base that contains the preferences, characteristics, and activities of the user. A user profile can be built from a set of keywords that describe the user preferred interest areas compared against information items.

User profiling can either be *static*, when it contains information that rarely or never changes (e.g. demographic information), or *dynamic*, when the data change frequently. Such information is obtained either *explicitly*, using online registration forms and questionnaires resulting in static user profiles, or *implicitly*, by recording the navigational behaviour and / or the preferences of each user. In the case of implicit acquisition of user data, each user can either be regarded as a member of group and take up an aggregate user profile or be addressed individually and take up an individual user profile. The data used for constructing a user profile could be distinguished into: (a) the Data Model which could be classified into the demographic model (which describes who the user is), and the transactional model (which describes what the user does); and (b) the Profile Model which could be further classified into the factual profile (containing specific facts about the user derived from transactional data, including the demographic data, such as "the favorite beer of customer X is Beer A"), and the behavioral profile (modeling the behavior of the user using conjunctive rules, such as association or classification rules. The use of rules in profiles provides an intuitive, declarative and modular way to describe user behavior [Adomavicious & Tuzhilin, 1999]).

Still, could current user profiling techniques be considered complete incorporating only these dimensions? Do designers and developers of Web-based applications take into consideration the real users' preferences in order to provide them a really personalized Web-based content? Many times this is not the case. How can a user profiling be considered complete, and the preferences derived optimized, if it does not contain parameters related to the user perceptual preference characteristics? We could define *User Perceptual Preference Characteristics* as all the critical factors that influence the visual, mental and emotional processes liable of manipulating the newly information received and building upon prior knowledge, that is different for each user or user group. These characteristics determine the visual attention, cognitive and emotional processing taking place throughout the whole process of accepting an object of perception (stimulus) until the comprehensive response to it [Germanakos et al., 2005].

In further support of the aforementioned concepts, one cannot disregard the fact that, besides the parameters that constitute the "traditional" user profile (composed of parameters like knowledge, goals, background, experience, preferences, activities, demographic information, socio-economic characteristics, device-channel characteristics 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 [Graber, 2000]. 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" [McLoughlin, 1999], 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 [Pithers, 2002]. 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 Web-based informational environment, the significance of the fore mentioned users' differences, both physiological and preferential, is distinct and should be taken into consideration when designing such adaptive environments.

It is true that nowadays, there are not researches that move towards the consideration of user profiling incorporating optimized parameters taken from the research areas of visual attention processing and cognitive psychology in combination. Some serious attempts have been made though on approaching e-Learning systems providing adapted content to the students but most of them are lying to the analysis and design of methodologies that consider only the particular dimension of cognitive learning styles, including Field Independence vs. Field Dependence, Holistic-Analytic, Sensory Preference, Hemispheric Preferences, and Kolb's Learning Style Model [Yuliang & Dean, 1999], applied to identified mental models, such as concept maps, semantic networks, frames, and schemata [Ayersman & Reed, 1998; Reed et al., 1996]. In order to deal with the diversified students' preferences such systems are matching the instructional materials and teaching styles with the cognitive styles and consequently they are satisfying the whole spectrum of the students' cognitive learning styles by offering a personalized Web-based educational content.

4 The Proposed Comprehensive User Profiling

Based on the abovementioned considerations we introduce the Comprehensive 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 Comprehensive User Profiling could be considered as the main raw content filtering module of an Adaptive Web-based Architecture. At this module all the requests are processed, being responsible for the custom tailoring of information to be delivered to the 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 [Panayiotou & Samaras, 2004]. The whole processing varies from security, authentication, user segmentation, content identification, user perceptual characteristics (visual, cognitive and emotional processing parameters) and so forth. This module could accept requests from an 'Entry Point' module and after the necessary processing and further communication with a 'Semantic Web-based Content' module, to provide the requested adapted and personalized result. The Comprehensive User Profiling is comprised of two main components:

4.1 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 capacity, latency (high / low), and battery lifetime. These characteristics are mostly referred to mobile users and are considered important for the formulation of a more integrated user profile, since it determines the technical aspects of it). Both elements are completing the user profiling from the user's point of view.

4.2 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 completes the user preferences and fulfills 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 attentional visual field and going through a number of cognitive, learning and emotional processes giving the actual response to that stimulus, as depicted in Fig. 1, below. As it can be observed, its primary parameters formulate a three-dimensional approach to the problem. The first dimension investigates the visual and cognitive processing of the user, the second his / her learning style, while the third captures his / her emotionality during the interaction process with the information space.

It is considered a vital component of the user profiling since it identifies the aspects of the user that is very difficult to be revealed and measured but, however, might determine his / her exact preferences and lead to a more concrete, accurate and optimized user segmentation. As mentioned above, it is composed of three elements:

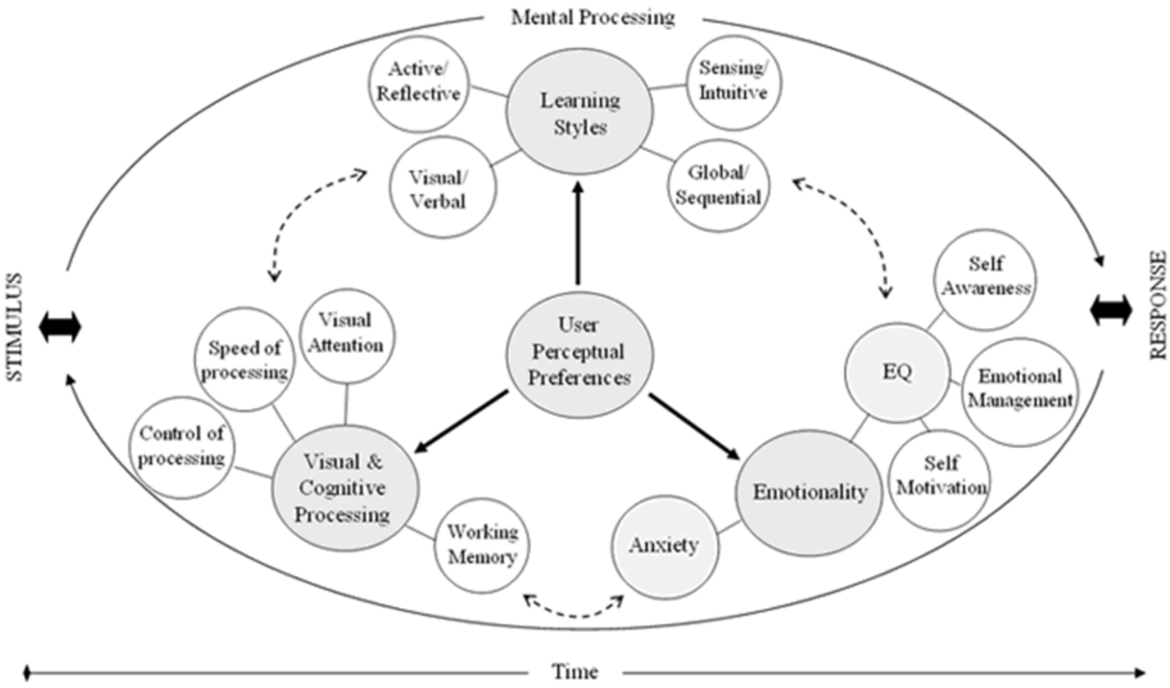

Figure 1. User Perceptual Preference Characteristics – Three-Dimensional Approach

(a) *Visual & Cognitive Processing*: From the *Visual Processing* special emphasis is given to the visual attention that is responsible for the tracking of the user's eye movements and in particular the scanning of his / her eye gaze on the information environment [Gulliver & Ghinea, 2004]. It is composed of two 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 [Demetriou et al., 1993; Demetriou & Kazi, 2001] 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, as it is depicted in Fig. 2a, the processing development speed increases non-linearly in the age of 0 – 15 (1500 msec), it is further stabilized in the age of 15 - 55-60 (500 msec) and decreases from that age on (1500 msec). However, it should be stated that the actual cognitive processing speed efficiency is yielded from the difference (maximum value 0.8 msec) between the peak value of the speed of processing and the peak value of control of processing, as it is depicted in Fig. 2b.

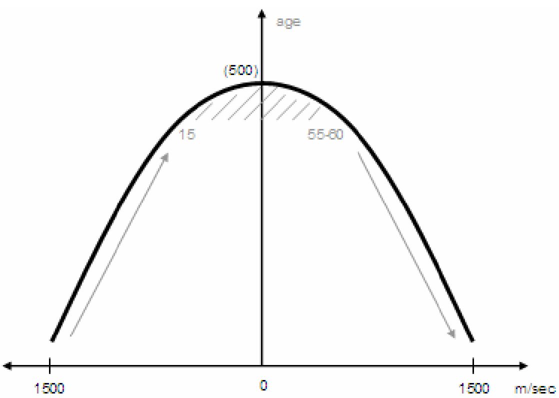

Figure 2a. Speed of Processing

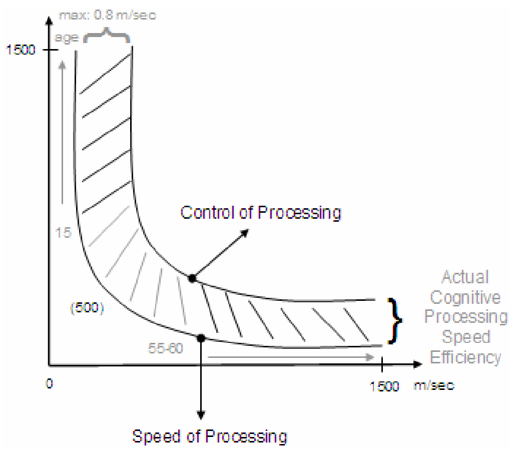

Figure 2b. Actual Cognitive Processing Speed Efficiency

(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. By taking into account these preferences and defining specific learning strategies, empirical research has shown that more effective learning can be achieved [Boyle et al., 2003], and that learning styles nevertheless correlate with performance in an e-learning web-based environment [Wang et al., 2006]. A selection of the most appropriate and technologically feasible learning styles (those that can be projected on the processes of selection and presentation of web-content and the tailoring of navigational tools) has been studied, such as Riding's Cognitive Style Analysis (Verbal-Imager and Wholistic-Analytical) [Riding, 2001], Felder / Silverman Index of Learning Styles (4 scales: Active vs Reflective, Sensing vs Intuitive, visual vs Verbal and Global vs Sequential) [Felder & Silverman, 1988], Witkin's Field-Dependent and Field-Independent [Witkin et al., 1977], and Kolb's Learning Styles (Converger, Diverger, Accommodator, and Assimilator) [Kolb & Kolb, 2005], in order to identify how users transforms information into knowledge (constructing new cognitive frames).

We consider that Riding's CSA and Felder / Silverman's ILS implications can be mapped on the information space more precisely, since they are consisted of distinct scales that respond to different aspects of the Web-space (see also Fig.4). Learning style theories that define specific types of learners, as Kolb's Experiential Learning Theory, have far more complex implications, since they relate strongly with personality theories, and therefore cannot be adequately quantified and correlated easily with web objects and structures.

Their main characteristics as well as their implication into the information space are summarized in Fig. 3a, 3b [Henke, 2001; Sharp, 1998; Liu & Ginther, 1999; Hong & Kinshuk, 2004].

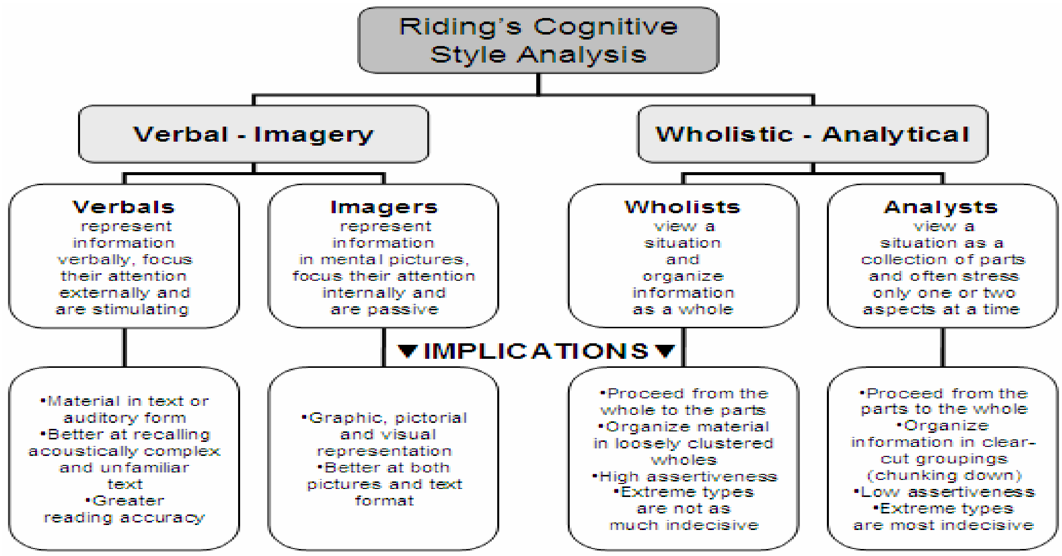

Figure 3a. Riding's Learning Styles Characteristics and Implications

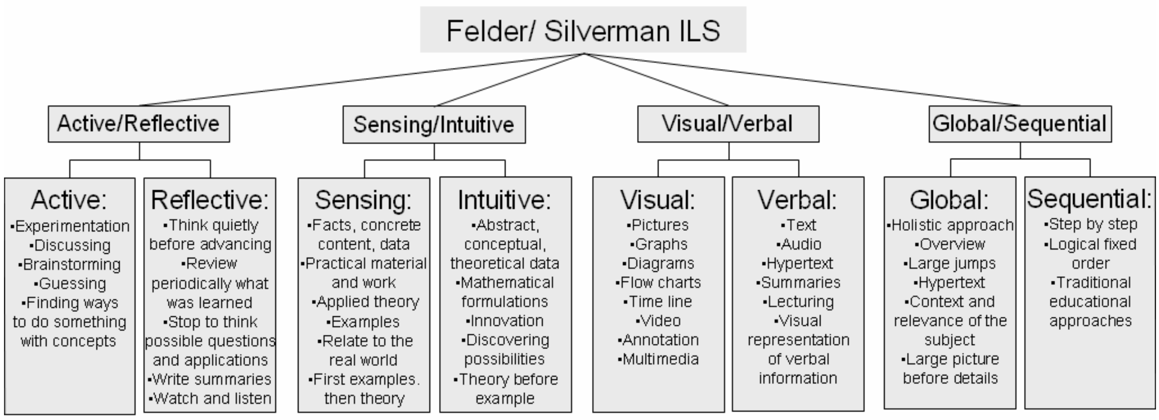

Figure 3b. Felder / Silverman ILS Scales' Characteristics / Implications

(c) *Emotionality*: An effort to construct a model that predicts the role of emotion, in general, is beyond the scope of our research, due to the complexity and the numerous confiding variables that would make such an attempt rather impossible. However, there is a considerable amount of references concerning the role of emotion and its implications on academic performance (or achievement), in terms of efficient learning [Kort & Reilly, 2002]. Emotional Intelligence seems to be an adequate predictor of the aforementioned concepts, and is surely a grounded enough construct, already supported by academic literature.

On the basis of the research conducted by Goleman (1995), as well as Salovey & Mayer (1990), who have introduced the term, we are in the process of developing an EQ questionnaire that examines the 3 out of 5 scales that comprise the Emotional Intelligence construct (according to Goleman), since factors that deal with human to human interaction (like empathy) are not present in our web- application - at least for the time being.

As a result, our variation of the EQ construct, which we refer to as Emotional Control, consists of:

- The Self- Awareness scale
- The Emotional Management scale
- The Self- Motivation scale

While our sample is still growing, Crombach's alpha, which indicates scale reliability, is currently 0.714. Revisions on the questionnaire are expected to increase reliability.

Still, there is a question about the role of primary / secondary emotions, and their cognitive and / or neurophysiologic intrinsic origins [Damasio, 1994]. Emotions influence the cognitive processes of the individual, and therefore have certain effect in any educational setting. Again, bibliographic research has shown that anxiety is often correlated with academic performance [Cassady, 2004], as well with performance in computer mediated learning procedures [Smith & Caputi, 2005; Chang, 2005]. Subsequently, different levels of anxiety have also a significant effect in cognitive functions.

We believe that combining the level of anxiety of an individual with the moderating role of Emotional Control, it is possible to clarify, at some extent, how affectional responses of the individual hamper or promote learning procedures. Thus, by personalizing educational content on emotionality, we can avoid stressful instances and take full advantage of his / hers cognitive capacity at any time.

There are two ways to measure anxiety. Firstly, with anxiety questionnaires, many of them dealing with anxiety at educational settings, providing information about how an individual reacts when is obliged to learn or to go through exams (cognitive test anxiety). Still, since we are interested also in his emotional state during the web-based learning procedures, real- time monitoring of anxiety levels would also provide us useful indications. That can be done by a self-reporting instrument (e.g. by giving the user the possibility to define his anxiety level on a bar shown on the computer screen), and / or by specially designed gadgets that measure heart rate, sweat and other physical evidence.

We intend to use all these methods of measurement, as the main direction of our future work, controlling at the same time confiding or correlated variables like verbal ability (and / or IQ). We primarily aim to ground our hypothesis that personalizing web content according to the participants' emotional characteristics (an individual's capability or incapability to control his / hers emotions and use anxiety in a constructing way), is of high significance in optimizing computer mediated learning processes.

For a better understanding of the three dimensions' implications and their relation with the information space a diagram that presents a high level correlation of these implications with selected tags of the information space (a code used in web languages to define a format change or hypertext link) is depicted in Fig. 4. These tags (images, text, information quantity, links, extra navigation support, aesthetics, and position of data on the screen) have gone through an extensive optimization representing group of data affected after the mapping with the implications. The particular mapping is based on specific rules created, liable for the combination of these tags and the variation of their value in order to better filter the raw content and deliver the most personalized Web-based result to the user.

As it can be observed from the diagram below each dimension has primary (solid line) and secondary (dashed line) implications on the information space altering dynamically the weight of the tags. It has to be mentioned at this point that we consider that this Data – Implications Diagram can be applied on multiple research fields (other than educational). Therefore, we include in the Learning Styles dimension Riding's Cognitive Style Analysis, which applies in a greater number of information distribution circumstances, since it deals rather with cognitive than learning style. Henceforth, for example, the number of images (few or many) to be displayed has a primary implication on Imagers, while text (more concise or abstract) has a secondary implication. An Analyst may affect primarily the Links – Learner Control tag while might secondary affect the number of images or kind of text to be displayed as well as the degree of navigation support which, consequently, is primarily affected by low Emotionality. Emotionality along with Visual Attention are primarily affecting the aesthetics tags, determining the presentation schemes of the data displayed to the users. The Position of Data on the Screen tag is primarily correlated to the Visual Attention. The particular correlation (shaded) will be treated with a different experimentation approach; with the use of an eye-tracker gadget we will try to identify particular eye gaze paths of the users and therefore positioning the adapted information on the preferred part on the screen.

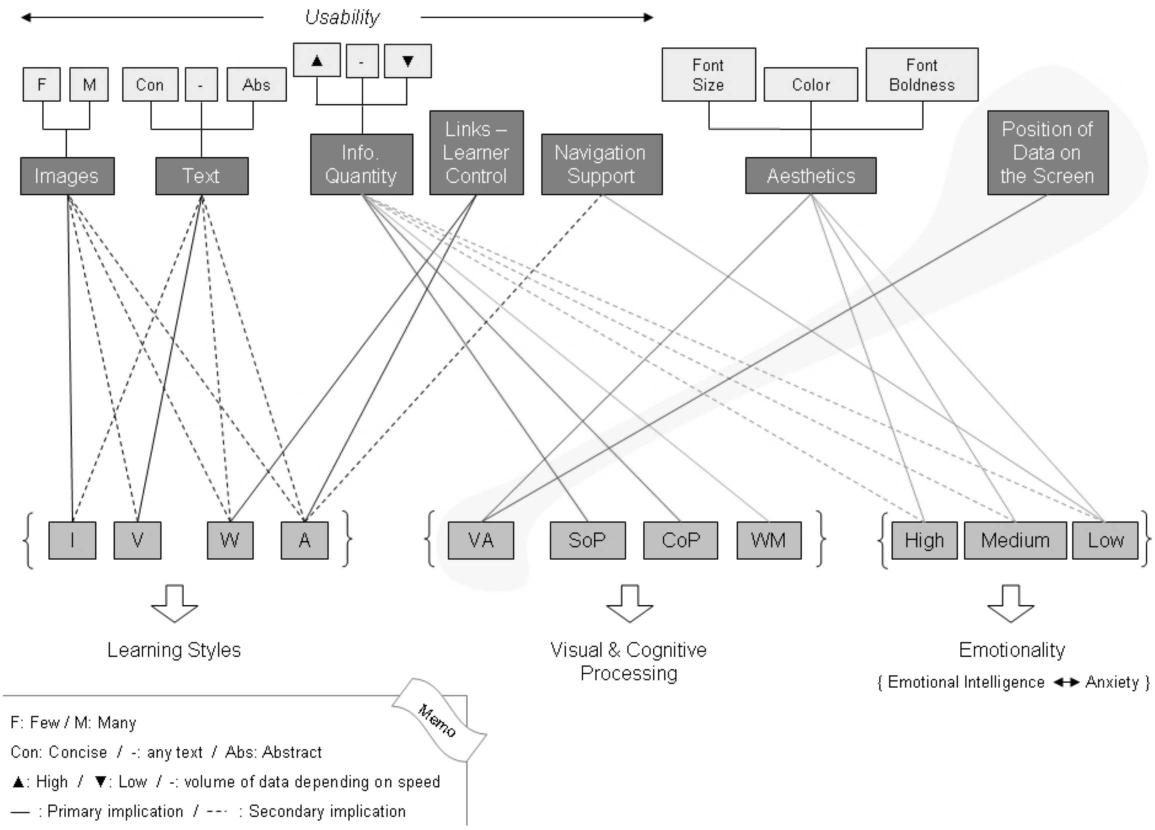

Figure 4. Data – Implications Correlation Diagram

A practical example of the Data – Implications Correlation Diagram could be as follows, a user might be identified that is: (a) Verbalizer (V) – Wholist (W) with regards to the Learning Style, (b) has a Cognitive Processing speed (Speed of Processing (SoP) and Control of Processing (CoP)) of 1000 msec, a fair Working Memory (weighting 5/7) with his / her Visual Attention (VA) to usually focusing on the up-right corner of the screen, and (c) (s)he has a Low Emotionality. The tags affected, according to the rules created and the Data – Implications Correlation Diagram, for this particular instance are the: Images (few images displayed), Text (any text could be delivered), Info Quantity (less info since his / her cognitive speed is moderate), Links – Learner Control (high learner control because (s)he is Wholist), Navigation Support (significant because (s)he has low emotionality), high aesthetics (to give more structured and well defined information, with more colors, larger fonts, more bold text, since (s)he has low emotionality), and Position of Data on the Screen (display important info on the up-right corner of the screen). At this point it should be mentioned that in case of internal correlation conflicts primary implications take over secondary ones. Additionally, since Emotionality is the most dynamic parameter compared to the others, any changes occurring at any given time are directly affecting the yielded value of the adaptation and personalization rules and henceforth the format of the content delivered.

4.3 The Comprehensive User Profiling Construction

All the components and parameters constituting the Comprehensive User Profiling have extensively investigated and further optimized based on criteria related to their implementation into the information space. The basic information flow of the architecture that will enable the construction of the Comprehensive User Profiling is shown below in Fig. 5.

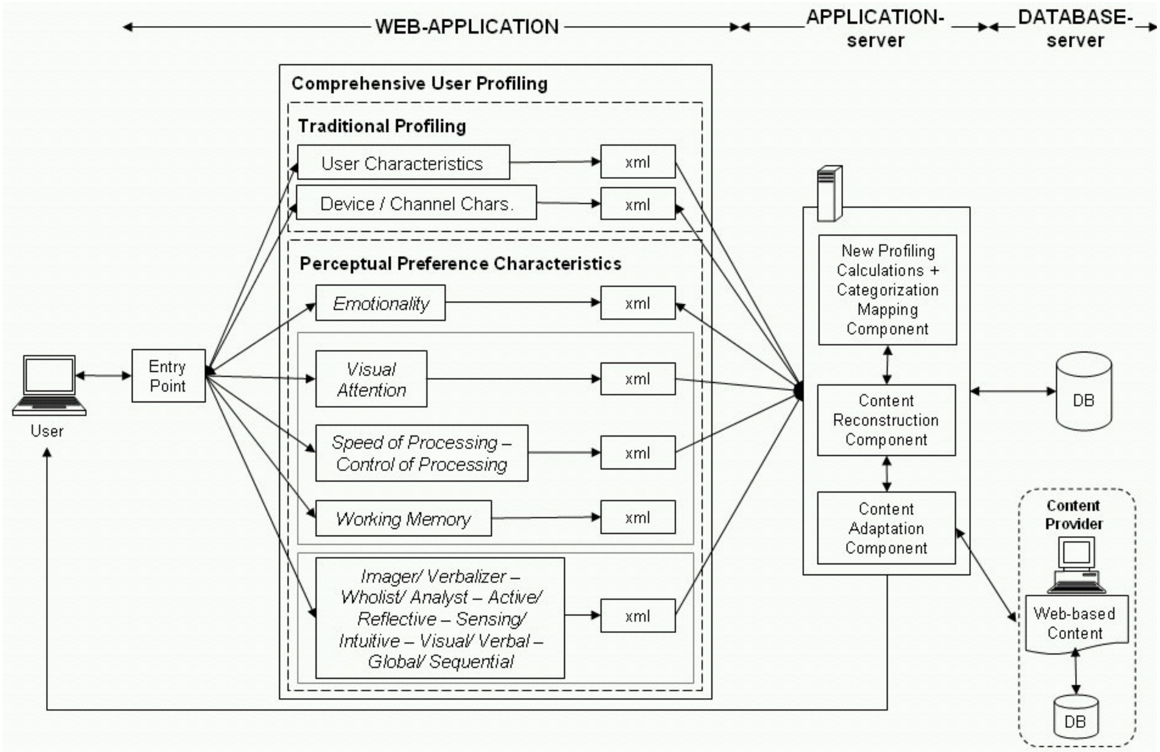

Figure 5. The Comprehensive User Profiling Construction

As it can be clearly observed it concerns a three-tier architecture that is composed of the Web-Application tier (client-side), the Application-Server tier, and the Database-Server tier. The main reason for building the particular system this way is due to the fact that the primary concern is to achieve maximum interoperability and integration of the various heterogeneous tests implemented.

Taking a closer look to the Comprehensive 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 (i.e. identifying emotionality) and others with real time interaction metrics (online tests identifying the users cognitive processing speed efficiency, working memory, visual attention, and learning styles).

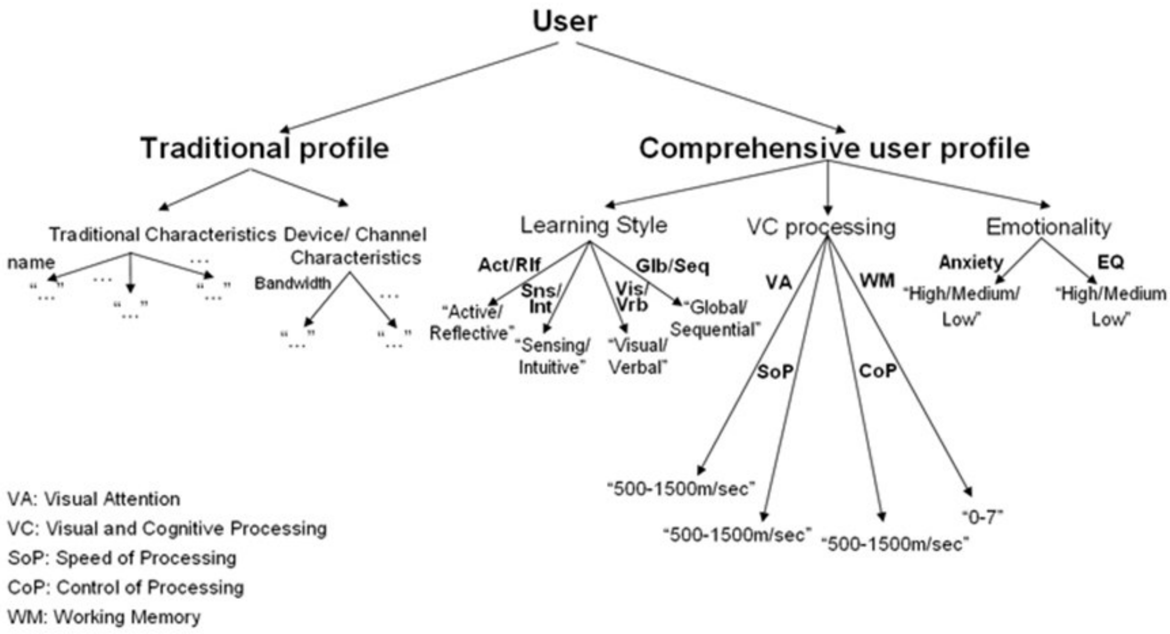

Figure 6. The Tree Structure of the Comprehensive User Profiling XML document

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 Comprehensive User Profiling, giving emphasis on the comprehensive user profile structure, is depicted in Fig. 6.

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 Application-Server tier to run properly Web-based content is conveyed from the provider's application in the form of metadata.

Once the provided content is altered according to user characteristics, the system displays 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.

5 Experimental Implementation Considerations based on Specific Cognitive Learning Styles

In order to assess the aforementioned importance of learning and cognitive styles over performance in educational environments, we designed an experiment on the field of adaptive e-learning [Tsianos et al., 2005]. 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 educational content delivery systems.

We conducted our experiment within an e-learning 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 like previous knowledge and experience, by selecting an undergraduate course on algorithms at our department, where 1st year students have absolutely no background and traditionally perform poorly. In order to classify students according to their learning style, we used the Felder / Soloman Index of Learning Styles (ILS) [Felder & Silverman, 1988]. 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 also indicates the strength of each person's preference on the scale (low, medium, high). Additionally, considering circumstantial and convenience factors, we used the ILS.

The Felder / Silverman theory [Felder & Spurlin, 2005] 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. The intuitive students were 26, while the sensing 38, and most importantly medium and high intuitive students were almost equal to medium and high sensing (16 vs 15). Unexpectedly, students were mostly intermediates on the other 3 scales, which was very convenient in terms of controlling variables.

As a result, we focused on that dimension, sensing intuitive that is, expecting to see noticeable differences in their information retaining (or learning) performance, depending on how intuitive or sensing the students are. Consequently, we designed an 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.

5.1 The 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 educational 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.

5.1.1 Overall results (N=70)

We found that the score that each subject achieved on the Index of Learning Styles sensing / intuitive (SI) scale was significantly correlated with his / her performance on the exams. Those with a negative score on the 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).

Correlations

			Sensing-Intuitive	SCORE
Spearman's rho	Sensing-Intuitive	Correlation Coefficient	1,000	-,349**
		Sig. (1-tailed)	,	,002
		N	70	70
	SCORE	Correlation Coefficient	-,349**	1,000
		Sig. (1-tailed)	,002	,
		N	70	70

**. Correlation is significant at the .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 educational 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 sequentials. 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.

5.1.2 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 educational 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).

Correlations

			Sensing-Intuitive	SCORE
Spearman's rho	Sensing-Intuitive	Correlation Coefficient	1,000	-,501**
		Sig. (1-tailed)	,	,002
		N	32	32
	SCORE	Correlation Coefficient	-,501**	1,000
		Sig. (1-tailed)	,002	,
		N	32	32

**. Correlation is significant at the .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.

5.1.3 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
- 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 an educational 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.

6 Conclusion and Future Trends

The basic objective of this paper was to introduce a combination of concepts coming from different research areas all of which focusing upon the user. It has been attempted to approach the theoretical considerations and technological parameters that can provide the most comprehensive user profiling, under a common filtering element (User Perceptual Preference Characteristics), supporting the provision of the most apt and optimized user-centered Web-based result.

This paper made an extensive reference to the adaptation of Web-based content delivery investigating characteristics of user-centered content delivery and the adaptation and personalization considerations with regards to new user requirements and demands. It underpinned the significance of the user profiling introducing the 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 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.

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 conduct experiments identifying the cognitive processing speed and visual attention processing efficiency of users as well as intrinsic parameters of emotionality. We will also investigate constraints and challenges arise from the implementation of such issues on mobile devices and channels. We will finally study the structure of the metadata coming from the providers' side, aiming to construct a Web-based personalization architecture that will serve as an automatic filter adapting the received content based on the comprehensive user profiling. The final system will provide a complete adaptation and personalization Web-based solution to the users satisfying their individual needs and preferences.

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