Chapter I
An Assessment of Human Factors in Adaptive Hypermedia Environments

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ABSTRACT

The plethora of information and services as well as the complicated nature of most Web structures intensify the navigational difficulties that arise when users navigate their way through this large information space. Personalized services that are highly sensitive to the immediate environment and the goals of the user can alleviate the orientation and presentation difficulties experienced by the relatively diverse user population. User profiles serves as the main component of most Web personalization systems. Main scope of this chapter is to present the various techniques employed by such systems with regards to user profiles extraction and introduce a comprehensive user profile, which includes User Perceptual Preference Characteristics. It further analyzes the main intrinsic users' characteristics like visual, cognitive, and emotional processing parameters incorporated as well as the "traditional" user profile characteristics that together tend to give the most optimized personalization outcome. It finally overviews a Web adaptation and personalization system and presents evaluation results that further support the importance of human factors in the information space.

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INTRODUCTION

The unprecedented and constant expansion of the World Wide Web coupled with the obscure and multi-component nature of its structure, result 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. As the e-Services sector is rapidly evolving, the need for such Web structures that satisfy the heterogeneous needs of its users is becoming more and more evident.

To alleviate such navigational and presentation difficulties, researchers have put huge amounts of effort to identify the peculiarities of each user group and analyze and design methodologies and systems that could deliver up-to-date adaptive and personalized information, with regards to products or services. Since to date, there has not been a concrete definition of personalization. The many adaptive hypermedia and Web personalization solutions offering personalization 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). Further consideration and analysis of parameters and contexts such as users intellectuality, mental capabilities, socio-psychological factors, emotional states and attention grabbing strategies, that could affect the apt collection of users' customization requirements offering in return the best adaptive environments to their preferences and demands should be extensively investigated. All these characteristics, along with the "traditional" user characteristics that is, name, age, education, experience, etc., constitute a comprehensive user profile that serves as the ground element of most of these systems.

Some noteworthy, mostly commercial, applications in the area of Web personalization that collects information with various techniques from the users based on which they construct their user profile and further adapt the services content provided, are amongst others the Broadvision's One-To-One, a commercial tool for identification of on-line users; Microsoft's Firefly Passport (developed by the MIT Media Lab); the Macromedia's LikeMinds Preference Server, which identifies behaviours of on-line customers and it further predicts new purchases of a user; Apple's WebObjects, which adapts the content to user preferences, etc. Other, more research oriented systems, include ARCHIMIDES (Bogonicolos et al., 1999), which adapts the raw content based on the structure reorganization of a Web server. The structure is depicted as a semantic tree through of which there is a dynamic selection of the content nodes according to the users' preferences; Proteus (Anderson et.al., 2001), is a system that construct user models using artificial intelligence techniques and adapts the content of a Web site taking into consideration also wireless connections; WBI (Maglio & Barret, 2000; Barret et. al, 1997) and BASAR (Thomas & Fischer, 1997), use static agents for the personalization of the content while other systems employ mobile agents over mobile networks for this purpose, like mPERSONA (Panayiotou & Samaras, 2003). Significant implementations have also been developed in the area of adaptive hypermedia, with regards to the provision of adapted educational content to students using various adaptive hypermedia techniques. Such systems are amongst others, INSPIRE (Papanikolaou et al., 2003), ELM-ART (Weber & Specht, 1997), AHA! (De Bra & Calvi, 1998), Interbook (Brusilovsky et. al., 1998), and so on.

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-eco-

nomic 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). 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 moving 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.

This chapter overviews adaptive hypermedia and Web personalization, investigating their relationship and presenting techniques used to monitor and extract user profiles which serves as their most essential and common element. Furthermore, it outlines the importance of user profiles and presents a comprehensive user profile that incorporates intrinsic user characteristics, such as user perceptual preferences (visual, cognitive and emotional processing parameters), on top of the "traditional" ones. Eventually, it introduces an adaptation and personalization architecture, AdaptiveWeb, emphasizing on the significance and peculiarities of the various user profiles aspects it employs, considered necessary for the provision of a most optimized personalization Web-based result. Based on this system, a further evaluation analysis is presented revealing the impact of human factors in the information space.

ADAPTIVE HYPERMEDIA OVERVIEW

Adaptivity is a particular functionality that alleviates navigational difficulties by distinguishing between interactions of different users within the information space (Eklund & Sinclair, 2000; Brusilovsky & Nejdl, 2004). Adaptive Hypermedia Systems employ adaptivity by manipulating the link structure or by altering the presentation of information, based on a basis of a dynamic understanding of the individual user, represented in an explicit user model (Eklund & Sinclair, 2000; De Bra et al., 1999; Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky, 1996b). In the 1997 discussion forum on Adaptive Hypertext and Hypermedia, an agreed definition of adaptive hypermedia systems was reached after Brusilovsky (Eklund & Sinclair, 2000) as follows: "By Adaptive Hypermedia Systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible and functional aspects of the system to the user" (Eklund & Sinclair, 2000; Brusilovsky, 1996b).

A system can be classified as an Adaptive Hypermedia System if it is based on hypermedia, has an explicit user-model representing certain characteristics of the user, has a domain model which is a set of relationships between knowledge elements in the information space, and is capable of modifying some visible or functional part of the system based on the information maintained in the user-model (Eklund & Sinclair, 2000; Brusilovsky & Nejdl, 2004; Brusilovsky, 1996b).

In 1996, Brusilovsky identified four user characteristics to which an Adaptive Hypermedia System should adapt (Brusilovsky, 1996b; Brusilovsky, 2001). These were user's knowledge, goals, background and hypertext experience, and user's preferences. In 2001, further two sources of adaptation were added to this list, user's interests and individual traits, while a third source of different nature having to deal with the user's

environment had also been identified.

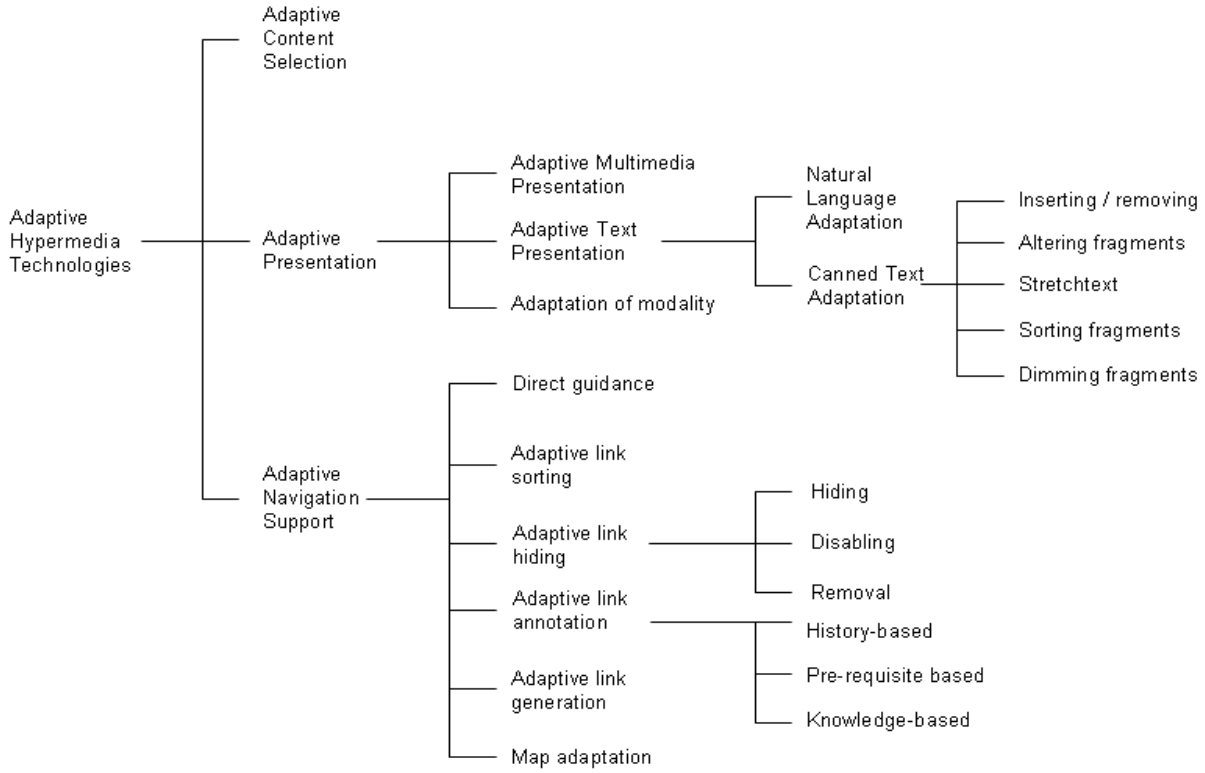
Generally, Adaptive Hypermedia Systems can be useful in application areas where the hyperspace is reasonably large and the user population is relatively diverse in terms of the above user characteristics (Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky and Nejdl, 2004; Brusilovsky, 1996b). A review by Brusilovsky has identified six specific application areas for adaptive hypermedia systems since 1996 (Brusilovsky, 2001). These are educational hypermedia, on-line information systems, information retrieval systems, institutional hypermedia and systems for managing personalized view in information spaces. Educational hypermedia and on-line information systems are the most popular, accounting for about two thirds of the research efforts in adaptive hypermedia.

Adaptation effects vary from one system to another. These effects are grouped into three major adaptation technologies - adaptive content selection (Brusilovsky & Nejdl, 2004), adaptive presentation (or content-level adaptation) and adaptive navigation support (or link-level adaptation) (Eklund & Sinclair, 2000; De Bra et al., 1999; Brusilovsky, 2001; Brusilovsky & Peylo, 2003; Brusilovsky, 1999; Brusilovsky, 1996a; Brusilovsky, 1996b; Brusilovsky & Nejdl, 2004; Brusilovsky, 2003; Bailey *et al*., 2002; Brusilovsky & Pesin, 1998; Bulterman et al., 1999) and are summarized in Figure 1.

The first of these three technologies comes from the field of adaptive information retrieval (IR) and is associated with a search-based access to information. When the user searches for relevant information, the system can adaptively select and prioritize the most relevant items (Brusilovsky & Nejdl, 2004).

The idea of adaptive presentation is to adapt the content of a page to the characteristics of the user according to the user model (Eklund &

Figure 1. Adaptive hypermedia techniques



Sinclair, 2000; De Bra *et al*., 1999; Brusilovsky, 2001; Brusilovsky & Pesin, 1998). With such techniques the content is individually generated or assembled from pieces for each user, to contain additional information, pre-requisite information or comparative explanations by conditionally showing, hiding, highlighting or dimming fragments on a page (De Bra *et al*., 1999). The granularity may vary from word replacement to the substitution of pages to the application of different media. Adaptive presentation techniques have been classified into: (a) adaptive multimedia presentation, (b) adaptive text presentation, and (c) adaptation of modality (Brusilovsky & Nejdl, 2004; Brusilovsky & Pesin, 1998).

Adaptive navigation techniques have been classified according to the way they adapt the presentation of links, ranging from methods that restrict the user's interactions with the content to techniques that aid the user in their understanding of the information space, aiming provide either orientation or guidance (Eklund & Sinclair, 2000). Orientation informs the user about their place in the hyperspace while guidance is related to a user's goal. These techniques are: direct guidance (Eklund & Sinclair, 2000; Brusilovsky & Pesin, 1998); adaptive link sorting (Eklund & Sinclair, 2000; Brusilovsky & Pesin, 1998); adaptive link hiding (Eklund & Sinclair, 2000; Brusilovsky & Pesin, 1998); adaptive link annotation (Brusilovsky & Pesin, 1998); adaptive link generation (Brusilovsky, 2001; Brusilovsky & Nejdl, 2004); and map adaptation (Brusilovsky, 1996b).

WEB PERSONALIZATION OVERVIEW

Web personalization is the process of customizing the content and structure of a Web site to the specific needs of each user by taking advantage of the user's navigational behaviour. Being a multi-dimensional and complicated area a universal definition has not been agreed to date. Nevertheless, most of the definitions given to personalization (Cingil et al., 2000; Blom, 2000; Kim, 2002; Wang & Lin, 2002) agree that the steps of the Web personalization process include: (1) the collection of Web data, (2) the modelling and categorization of these data (pre-processing phase), (3) the analysis of the collected data, and the determination of the actions that should be performed. Moreover, many argue that emotional or mental needs, caused by external influences, should also be taken into account.

Personalization could be realized in one of two ways: (a) Web sites that require users to register and provide information about their interests, and (b) Web sites that only require the registration of users so that they can be identified (De Bra et al., 2004). The main motivation points for personalization can be divided into those that are primarily to facilitate the work and those that are primarily to accommodate social requirements. The former motivational subcategory contains the categories of enabling access to information content, accommodating work goals, and accommodating individual differences, while the latter eliciting an emotional response and expressing identity (Wang & Lin, 2002). Personalization levels have been classified into: Link Personalization, Content Personalization, Context Personalization, Authorized Personalization and Humanized Personalization.

Link personalization involves selecting the links that are more relevant to the user, changing the original navigation space by reducing or improving the relationships between nodes. E-commerce applications use link personalization to recommend items based on the clients' buying history or some categorization of clients based on ratings and opinions. Link personalization is widely used in Amazon.com to link the home page with recommendations, new releases, shopping groups, etc. (Rossi et al., 2001).

When *content* becomes personalized, user interface can present different information for different users providing substantive informa-

tion in a node, other than link anchors. Most of the content personalization research is relative to text and hypertext personalization and can be further classified into two types: (a) Node structure customization (personalization), usually appears in those sites that filter the information that is relevant for the user, showing only sections and details in which the user may be interested. The user may explicitly indicate their preferences, or these may be inferred (semi-) automatically either from the user profile or navigation activity. For example, in my.yahoo.com or in www.mycnn.com users choose a set of "modules" and further personalize those modules by choosing a set of attributes of the module to be perceived. Some "automatic" customization may occur based on location information (e.g. by using the zip code of the user to select local to the user sport events). The outcome of these applications is that the user should be able to "build" their own page; and (b) Node content customization (personalization), occurs when different users perceive different values for the same node attribute; this kind of content personalization is finer grained than structure personalization. A good example can be found in online stores that give customers special discounts according to their buying history (in this case the attribute price of item is personalized) (Rossi et al., 2001).

Personalizing navigational *contexts* is critical when the same information (node) can be reached in different situations (Rossi et al., 2001). A navigational context is a set of nodes that usually share some property. For example in a Conference Paper Review Application, it is possible to access papers etc. Notice that one paper may appear in different sets and that different users may have different access restrictions according to their role in the Review application. Context personalization can also be adapted to the preferences of the learner and semantics of the learner's current environment. One sub-category of context personalization is terminal adaptivity. That is adapting information to the characteristics of a device. It is applied on the mobile devices to satisfy learner's demand for "learning as you go". Terminal Personalization occurs on a per session basis. Personalization can be achieved by applying many axes of adaptation effecting both the navigational structure and appearance of the learning experience. It involves the tailoring of a resource to the current environment of the learner (Lankhorst et al., 2002).

With *authorized* personalization, different users have different roles and therefore they might have different access authorizations. For example, in an academic application, instructors and students have different tasks to perform. Instructors want to access their class materials, such as upload, edit their class syllabus and give students' grades etc. On the other hand, students want to access the interface to find out their current GPA, their enrolment status, and their course work status etc.

Humanized personalization involves human computer interaction. If this dimension of the "emotional user interface" could be involved, it will be a huge step towards a concrete and universal definition of Web personalization. Unquestionably, this category of personalization still needs to be explored, with an extensive use of Artificial Intelligence technologies (Kaplan et al., 1999). Kaplan et al. (1999) made a first step towards exploring this area when they implemented an intelligent interactive telephone system (Telephone-Linked Care (TLC)) that provided information whether they were talking to a machine or to a person during TKC relationships with the TLC system (Hjelsvold et al., 2001).

Web Personalization Technologies

Some of the most common paradigms used for Web personalization and most broadly serving as methods to extract user profile are the following:

Content-Based Filtering

Systems that are implementing these kinds of techniques are solely based on individual users' preferences. The system tracks each user's behaviour and recommends items that are similar to items the user liked in the past. It is based on description analysis of the items rated by the user and correlations between the content of these items and user's preferences. It is an alternative paradigm that has been used mainly in the context of recommending items such as books, Web pages, news, etc. for which informative content descriptors exist (Pazzani, 2005; Basilico & Hofmann, 2004; Shardanand & Maes, 1995). This technique is primarily characterized by two weaknesses, content Limitations and over-Specialization. There are content limitations like IR methods that can only be applied to a few kinds of content, such as text and image, and the extent aspects can only capture certain aspects of the content. On the other hand content-based recommendation systems provide recommendations merely based on user profiles, therefore, users have no chance of exploring new items that are not similar to those items included in their profiles and thus leading to over-specialization. Consequently, some more drawbacks that have been identified in time are (Shahabi & Chen, 2003; Shardanand & Maes, 1995; Mobasher et al., 2002):

1. Search-based models build keyword, category, and author indexes offline, but fail to provide recommendations with interesting, targeted titles. They also scale poorly for customers with numerous purchases and ratings.
2. User input may be subjective and prone to bias.
3. Explicit (and non-binary) user ratings may not be available.
4. Profiles may be static and can become outdated quickly.
5. May miss other semantic relationships among objects.

At this point it would be noteworthy to mention a complementary technique of Content-based filtering, namely Social Information filtering. It essentially automates the process "word-of-mouth" recommendations: items are recommended to a user based upon values assigned by other people with similar taste. The system determines which users have similar taste via standard formulas for computing statistical correlations. Social Information filtering overcomes some of the limitations of content-based filtering. Items being filtered need not be amenable to parsing by a computer. Furthermore, the system may recommend items to the user which are very different (content-wise) from what the user has indicated liking before. Finally, recommendations are based on the quality of items, rather than more objective properties of the items themselves (Shardanand & Maes, 1995; Mobasher et al., 2002). Some of the most popular systems using content-based filtering are WebWatcher, and client-side agent Letizia (Lieberman, 1995).

Rule-Based Filtering

The users are asked to answer a set of questions. These questions are derived from a decision tree, so as the user proceeds to answer them. What he finally receives is a result (e.g. list of products) tailored to his/her needs. Content-based, rule-based, and collaborative filtering may also be used in combination, for deducing more accurate conclusions. Some of the rule-based filtering drawbacks are: User input may be subjective and prone to bias, explicit (and non-binary) user ratings may not be available, profiles may be static and can become outdated quickly, and for large systems it becomes burdensome to manage. Related interesting systems include Dell, Apple Computer, and Broadvision.

Collaborative Filtering

Systems invite users to rate the objects or divulge their preferences and interests and then return

information that is predicted to be of interest to them. This is based on the assumption that users with similar behavior (e.g. users that are rating similar objects) have analogous interests. There are two general classes of collaborative filtering algorithms, memory-based methods and model-based methods (Wang & Lin, 2002; Eirinaki & Vazirgiannis, 2003, Pazzani, 2005; Basilico & Hofmann, 2004). Moreover, the goals in a collaborative filtering system are basically focused upon the reduction of computation time, the increase of the extent in which predictions can be computed in parallel, and the increase of prediction accuracy. Collaborative filtering can further refine the process of giving each individual personal recommendation compared to rule-based filtering. It overcomes the drawbacks of the content-based filtering because it typically does not use the actual content of the items for recommendation. It usually works based on assumptions. With this algorithm the similarity between the users is evaluated based on their ratings of products, and the recommendation is generated considering the items visited by nearest neighbors of the user. In its original form, the nearest-neighbor algorithm uses a two-dimensional user-item matrix to represent the user profiles. This original form suffers from three problems, scalability, sparsity, and synonymy (Shahabi & Chen, 2003; Papagelis et al., 2004). Some more highlighted drawbacks of collaborative filtering are focused upon: (a) Collaborative-filtering techniques are often based in matching in real-time the current user's profile against similar records obtained by the systems over time from other users. However, as noted in recent studies, it becomes hard to scale collaborative filtering techniques to a large number of items, while maintaining reasonable prediction performance and accuracy. Part of this is due to the increasing sparsity in the data as the number of items increase. One potential solution to this problem is to first cluster user records with similar characteristics, and focus the search for nearest neighbors only in the matching clusters. In the context of Web personalization this task involves clustering user transactions identified in the preprocessing stage; (b) traditional collaborative filtering does little or no offline computation, and its online computation scales with the number of customers and catalog items. The algorithm is impractical on large data sets, unless it uses dimensionality reduction, sampling, or partitioning–all of which reduce recommendation quality; (c) user input may be subjective and prone to bias; (d) explicit (and non-binary) user ratings may not be available; (e) profiles may be static and can become outdated quickly; (f) they are not able to recommend new items that have not already been rated by other users. An object will become available for recommendation only when many users have seen it and rated it, making it part of their profiles first ("latency problem"); (g) they are not satisfactory when dealing with a user that is not similar enough with any of the existing users (Mobasher et al., 2002; Mobasher et al., 2000; Vozalis et al., 2001). Some systems applied with this technique are Yahoo, Excite, Microsoft Network, Net Perceptions, Amazon.com, and CDNOW.

Web Usage Mining

The typical sub-categorization of the Web mining research field falls into the following three categories: Web-content mining, Web-structure mining, and Web usage mining. The prerequisite step to all of the techniques for providing users with recommendations is the identification of a set of user sessions from the raw usage data provided by the Web server. Web usage mining is the only category related to Web Personalization. This process relies on the application of statistical and data mining methods to the Web log data, resulting in a set of useful patterns that indicate users' navigational behavior. The data mining methods that are employed are: Association rule-mining, sequential pattern discovery, clustering, and classification. Given the site map structure and

usage logs, a Web usage miner provides results regarding usage patterns, user behavior, session and user clusters, click stream information, and so on. Additional information about the individual users can be obtained by the user profiles (Deshpande & Karypis, 2004; Eirinaki & Vazirgiannis, 2003; Cingil et al., 2000). The overall process can be divided into two components. (a) The offline component is comprised of the pre-processing and data preparation tasks, including data cleaning, filtering, and transaction identification, resulting in a user transaction file, and (b) the data mining stage in which usage patterns are discovered via specific usage mining techniques such as association-rule mining, association-rule discovery and usage clustering (Mobasher et al., 2000). The increasing focus on Web-usage mining as the time passes derives from some key characteristics which are summarized as follows: (a) the profiles are dynamically obtained, from user patterns, and thus the system performance does not degrade over time as the profiles age; (b) using content similarly alone as a way to obtain aggregate profiles may result in missing important relationships among Web objects based on their usage. Thus, Web usage mining will reduce the need for obtaining subjective user ratings or registration-based personal preferences; (c) profiles are based on objective information (how users actually use the site); (d) there is no explicit user ratings or interaction with users (saves time and other complications); (e) it helps preserve user privacy, by making effective use of anonymous data; (f) the usage data captures relationships missed by content-based approaches; (g) it can help enhance the effectiveness of collaborative or content-based filtering techniques. Nevertheless, usage-based personalization can be problematic when little usage data is available pertaining to some objects or when the site content attributes of a site must be integrated into a Web mining framework and used by the recommendation engine in a uniform manner (Mobasher et al., 2002). Noteworthy applications are Alta-Vista, Lycos, WebSift, and SpeedTracer.

Demographic-Based Filtering

This specific technique could be roughly described as an approach that uses demographic information to identify the types of users that prefers a certain object and to identify one of the several pre-existing clusters to which a user belongs and to tailor recommendations based on information about others in this cluster (Pazzani, 2005; Basilico & Hofmann, 2004).

Agent Technologies

Agents are processes with the aim of performing tasks for their users, usually with autonomy, playing the role of personal assistants (Delicato et al. 2001; Panayiotou and Samaras, 2004). Agents usually solve common problems users experience on the Web such as personal history, shortcuts, page watching and traffic lights. Some of the agents' main characteristics could be distinguished according to their abilities used and according to the tasks they execute. The former include characteristics such as intelligence, autonomy, social capacity (inter-agent communication), and mobility; while the latter classify the agents into information filtering agents, information retrieval agents, recommendation agents, agents for electronic market, and agents for network management (Delicato et al. 2001). Pioneer personalization systems implemented with agents are: ARCHIMIDES, Proteus, WBI, BASAR, 1:1 Pro, Haystack, eRACE, mPersona, Fenix system, and SmartClient.

Cluster Models

These types of techniques are found mostly in the area of eCommerce and could be characterized as eCommerce recommendation algorithms. To find customers who are similar to the user, cluster models divide the customer base into many segments and treat the task as a classification problem. The algorithm's goal is to assign the

user to the segment containing the most similar customers. It then uses the purchases and ratings of the customers in the segment to generate recommendations. The segments typically are created using a clustering or other unsupervised learning algorithm, although some applications use manually determined segments. Using a similarity metric, a clustering algorithm groups the most similar customers together to form clusters or segments. Because optimal clustering over large data sets is impractical, most applications use various forms of greedy cluster generation. These algorithms typically start with an initial set of segments, which often contain one randomly selected customer each. They then repeatedly match customers to the existing segments, usually with some provision for creating new or merging existing segments. For very large data sets–especially those with high dimensionality–sampling or dimensionality reduction is also necessary. Once the algorithm generates the segments, it computes the user's similarity to vectors that summarize each segment, chooses the segment with the strongest similarity and classifies the user accordingly. Some algorithms classify users into multiple segments and describe the strength of each relationship (Perkowitz & Etzioni, 2003). Cluster models have better online scalability and performance than collaborative filtering because they compare the user to a controlled number of segments rather than the entire customer base. The complex and expensive clustering computation is run offline. However, recommendation quality is relatively poor. To improve it, it is possible to increase the number of segments, but this makes the online user segment classification expensive. Typical examples of eCommerce systems are Amazon.com, Dell, and IBM.com.

SIMILARITIES AND DIFFERENCES

After having seen a brief overview of Adaptive Hypermedia and Web Personalization and their methodologies employed to deliver an adapted and optimized content to the user, it would be essential at this point to spot out their similarities and differences. Furthermore, to identify their convergence point which is their objective to develop techniques to adapt what is presented to the user based on the specific user needs identified in the extracted user profile.

Generally, Adaptive Hypermedia refers to the manipulation of the link or content structure of an application to achieve adaptation and makes use of an explicit user model (Eklund & Sinclair, 2000; De Bra et al., 1999; Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky, 1996b). Adaptive Hypermedia is a relatively old and well established area of research counting three generations: The first "pre-Web" generation of adaptive hypermedia systems explored mainly adaptive presentation and adaptive navigation support and concentrated on modeling user knowledge and goals. The second "Web" generation extended the scope of adaptive hypermedia by exploring adaptive content selection and adaptive recommendation based on modeling user interests. The third "New Adaptive Web" generation moves adaptive hypermedia beyond traditional borders of desktop hypermedia systems embracing such modern Web trends as "mobile Web", "open Web", and "Semantic Web" (Brusilovsky, 2003). On the other hand, Web Personalization refers to the whole process of collecting, classifying and analyzing Web data, and determining based on these the actions that should be performed so that the user is presented with personalized information. As inferred from its name, Web Personalization refers to Web applications solely, and is a relatively new area of research. One could also argue that the areas of application of these two research areas are different, as Adaptive Hypermedia has found popular use in educational hypermedia and on-line information systems (Brusilovsky, 2001), where as Web Personalization has found popular use in eBusiness services delivery. From this, it could be inferred that Web Personalization has a

more extended scope that Adaptive Hypermedia, exploring adaptive content selection and adaptive recommendation based on modeling user interests. Also, the reason for the need of such areas to be researched is the quite similar.

The most evident technical similarity is that they both make use of a user model to achieve their goal. However, the way they maintain the user profile is different; Adaptive Hypermedia requires a continuous interaction with the user, while Web Personalization employs algorithms that continuously follow the users' navigational behavior without any explicit interaction with the user. Technically, two of the adaptation / personalization techniques used are the same. These are adaptive-navigation support (of Adaptive Hypermedia and else referred to as link-level adaptation) and Link Personalization (of Web Personalization) and adaptive presentation (of Adaptive Hypermedia and else referred to as content-level adaptation) and Content Personalization (of Web Personalization). Last but not least, it is noteworthy to mention that they both make use of techniques from machine learning, information retrieval and filtering, databases, knowledge representation, data mining, text mining, statistics, and human-computer interaction (Mobasher et al., 2007).

THE USER PROFILE IMPERATIVE

User profile serves as the core element of most systems and especially the adaptive and personalization ones. This prompts us to have a better insight of the user profile itself and the dimensions incorporated.

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).

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 profile 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 profile 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/her 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 profile 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.

CONSIDERING THE IMPORTANCE OF HUMAN FACTORS IN FURTHER COMPLETING THE USER PROFILE

Based on the abovementioned considerations we introduce the Comprehensive User Profile that combines the User Perceptual Preference Characteristics described above along with the "Traditional" User Profile Characteristics since they are affecting the way a user approaches an object of perception (Germanakos et al., 2007a).

The Comprehensive User Profile 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, 2006). 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 Profile is comprised of two main components:

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 profile from the user's point of view.

The User Perceptual Preference Characteristics

This is the new component / dimension of the user profile 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 Figure 2, 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

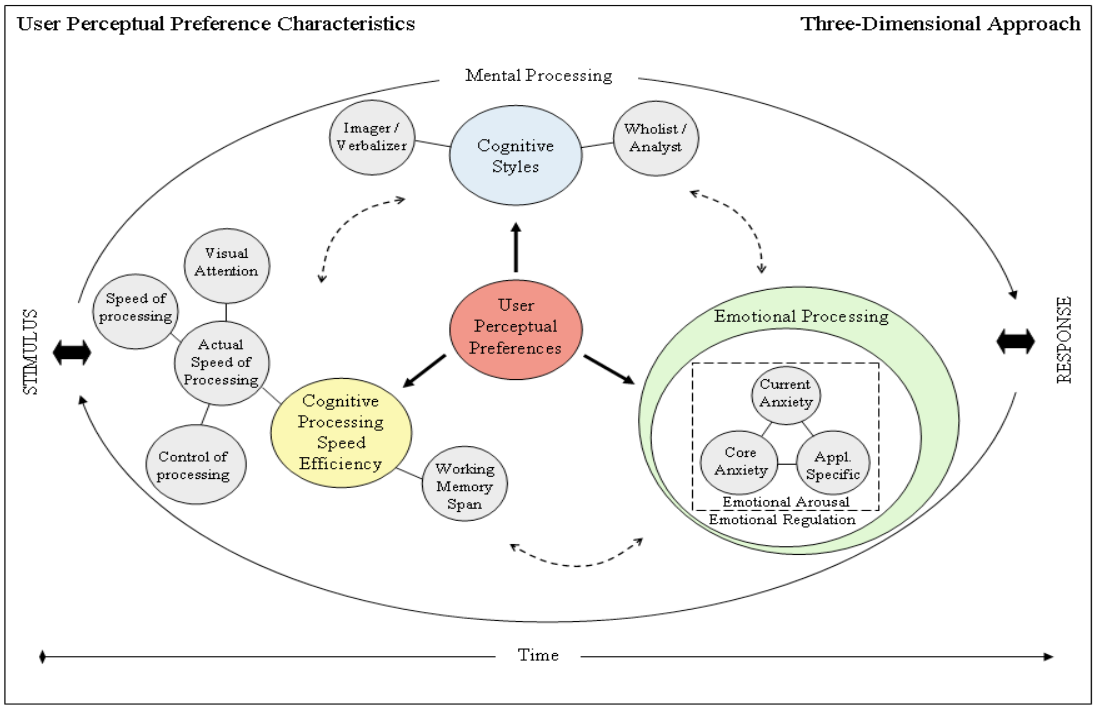
second his/her cognitive style, while the third captures his/her emotional processing during the interaction process with the information space (Germanakos et al., 2007a)

It is considered a vital component of the user profile 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:

Cognitive Processing Speed Efficiency

The Actual Speed of Processing parameters could be primarily determined by (i) the visual processing, whereby 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; (ii) the control of processing (refers to the processes that identify and register goal-relevant information and block out dominant or appealing but actually irrelevant in-

Figure 2. User perceptual preference characteristics: Three-dimensional approach



formation); and (iii) the speed of processing (refers to the maximum speed at which a given mental act may be efficiently executed). The Working Memory Span 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 Figure 3a, 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 Figure 3b.

Cognitive Style

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 physi-

Figure 3a. Speed of processing

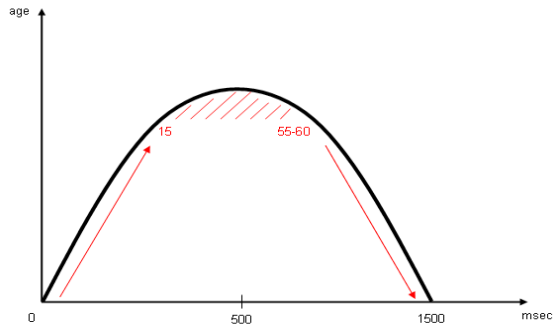
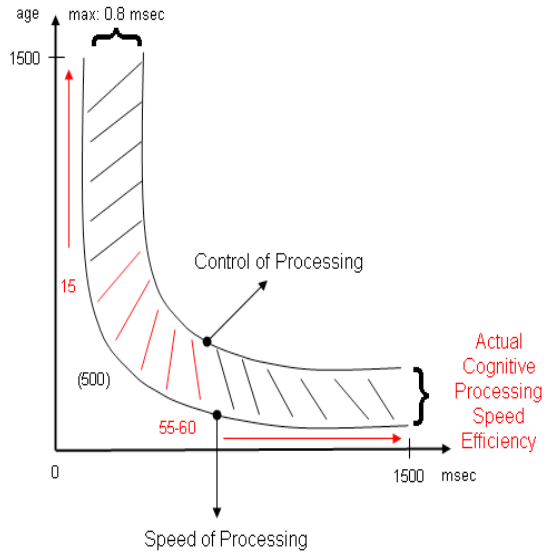


Figure 3b. Actual cognitive processing speed efficiency



ological 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 profile 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.

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 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), in order to identify how users transforms information into knowledge (constructing new cognitive frames).

The most prominent to be used seemed to be Riding's CSA since it can be mapped on the information space more precisely (the implications are consisted of distinct scales that respond to different aspects of the Web-space) and can be applied on most cognitive informational processing tasks (rather than strictly educational). The CSA implications are quite clear in terms of hypermedia design (visual/verbal content presentation and wholist/analyst pattern of navigation), and is probably one of the most inclusive theories, since it is actually derived from the common axis of a number of previous theories.

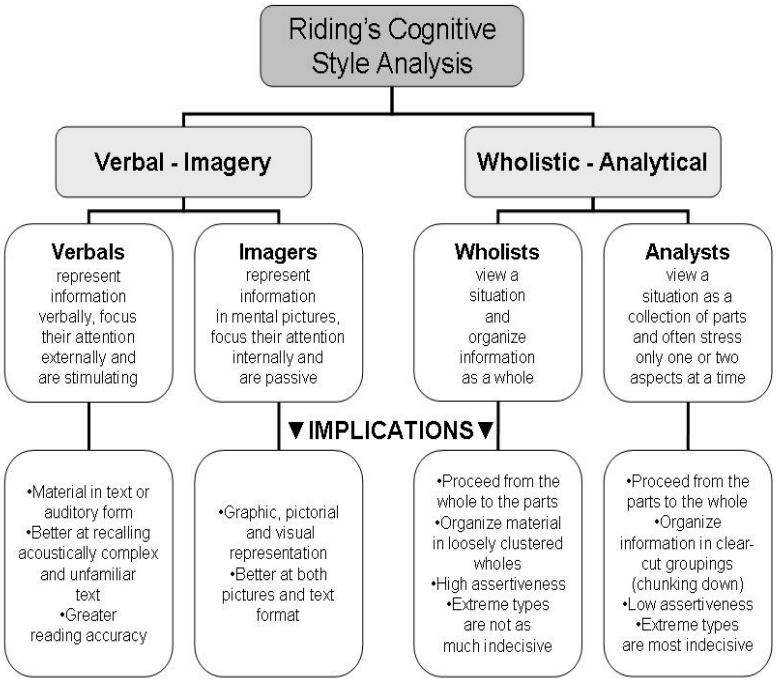
Learning style theories that define specific types of learners, as Kolb's Experiential Learning Theory, and Felder/Silverman's ILS (at least the active/reflective and sensing/intuitive scales) have far more complex implications, since they relate strongly with personality theories, and therefore cannot be adequately quantified and correlated easily with Web objects and structures.

The CSA main characteristics as well as their implication into the information space are summarized in Figure 4 (Sadler-Smith & Riding , 1999).

Emotional Processing

Research on modelling affect and on interfaces adaptation based on affective factors has matured considerably over the past several years, so that even designers of commercial products are now considering the inclusion of components that

Figure 4. Riding's cognitive learning styles characteristics and implications



take affect into account. Emotions are considered to play a central role in guiding and regulating behaviour and decision making, by modulating numerous cognitive and physiological activities. By coordinating specific instances of cognitive processing and physiological functioning, emotions are one of the tools that allow agents to make adaptive inferences in the design of Web-based systems.

In our study, we are interested in the way that individuals process their emotions and how they interact with other elements of their information-processing system. Emotional processing is a pluralistic construct which is comprised of two mechanisms: emotional arousal, which is the capacity of a human being to sense and experience specific emotional situations, and emotion regulation, which is the way in which an individual perceives and controls his/her emotions. We focus on these two sub-processes because they are easily generalized, inclusive and provide some indirect measurement of general emotional mechanisms. These sub-processes manage a number of emotional factors like anxiety boredom effects, anger, feelings of self efficacy and user satisfaction etc. Among these, our current research concerning emotional arousal emphasizes on anxiety, which is probably the most indicative, while other emotional factors are to be examined within the context of a further study.

Anxiety is an unpleasant combination of emotions that includes fear, worry and uneasiness and is often accompanied by physical reactions such as high blood pressure, increased heart rate and other body signals like shortness of breath, nausea and increased sweating. The anxious person is not able to regulate his/her emotional state since he feels and expects danger all the time. The systems underlying anxiety are being studied and examined continuously and it has been found that their foundations lie in the more primitive regions of the brain. However, given the complexity of the human nature, anxiety is characterized as a difficult to be understood construct of emotions

which is at a balance between nature and nurture and between higher perception and animal instinct.(Kim & Gorman, 1995).

Similar to Bandura's (1986) theory of self-efficacy, Barlow (2002) describes anxiety as a cognitive-affective process in which the individual has a sense of unpredictability, a feeling of uncertainty and a sense of lack of control over emotions, thoughts and events. This cognitive and affective situation is associated as well with physiological arousal and research has shown that an individual's perception is influenced in specific domains such as attentional span, memory, performance in specific tasks etc. In relation to performance, the findings are controversial. There is a number of studies that has shown no relationship between anxiety and performance, especially academic, although there is strong evidence that even if performance is not correlated with anxiety, they have indirect connection through a construct defined as cognitive effort. Although the final result is not altered, individuals with high anxiety level, in order to perform as required or fulfil the task assigned to them, need to try more, which means that they have to spend more of their cognitive resources. Performance is impaired in cases that the task is highly demanding and the individual needs to "mobilize" all his/her cognitive powers to respond. This way, the extra resources that would be probably needed because of high anxiety levels, would have been already occupied because of the demanding nature of the task itself. Another body of research supports that anxiety is strongly correlated to performance and academic achievement. High levels of anxiety impair concentration, attention, memory and finally performance itself. Low levels of anxiety mean lack of motivation, interest and goals.

Accordingly, in order to measure emotion regulation, we are using the cognominal construct of emotional regulation. 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 confounding 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. Additional concepts that were used are the concepts of self-efficacy, emotional experience and emotional expression.

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: (a) The Self- Awareness scale, (b) The Emotional Management scale, and (c) 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.

Self-efficacy is defined as people's beliefs about their capabilities to produce and perform. Self-efficacy beliefs determine how people feel, think, motivate themselves and behave. Such beliefs produce these diverse effects through four major processes. They include cognitive, motivational, affective and selection processes. *Emotional experience* is the conceptualization of an emotion, the way in which the individual is dealing with it and how he perceives it. *Emotional expression* is the way in which the individual is reacting after an emotion triggers. It is his/her behaviour after an affective stimulus. It can be argued that emotional expression is the representation of an emotion.

Still, there is a question about the role of emotions, and their cognitive and / or neuro-physiologic 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 emotional responses of the individual hamper or promote learning procedures. Thus, by personalizing Web-based content, taking into account emotional processing, we can avoid stressful instances and take full advantage of his/her cognitive capacity at any time.

Anxiety is a complex term and in order to measure it accurately and validly (measure the kind of anxiety we are interested in), it has to be adapted to our research. For this reason we included in our model not only a general anxiety measure (Stait-Trait Anxiety Inventory (STAI) test (Spielberger, 1983)) but a situation-specific measure of anxiety as well (i.e. educational). Additionally, we are interested in measuring anxiety as a predisposition (trait-anxiety) and as a generated (state-anxiety) set of emotions as well. This way, we can see the differences between the individual's evaluation of anxiety and what actually happens during the task. Individuals with high trait anxiety, report heightened perceptions of negative outcomes across a range of possible contexts and scenarios (Lerner and Keltner, 2000), so they tend to be subjective and negative to their judgement.

Still, since we are interested also in his/her emotional state during the Web-based learning procedures, real- time monitoring of anxiety levels (Current Anxiety) would also provide us useful indications. This is done by a self-reporting instrument (e.g. by giving the user the possibility to define his/her anxiety level on a bar shown on the computer screen).

Since our research examines learning process and how to improve performance through a personalization system, the situation-specific measure of anxiety that we are interested in is test anxiety. Test anxiety has been defined as one element of general anxiety composed of cognitive processes that interferes with performance in academic or assessment situations (Spielberger & Vagg, 1995). It includes both cognitive and physiological activity (Spielberger, 1972). Its two components are worry and emotionality. Worry is the cognitive concern about performance and emotionality is somatic reactions to task demands and stress (Schwarzer, 1984). Test anxiety research has shown a relationship between anxiety and performance (Sapp, 1993).

A DATA–IMPLICATIONS CORRELATION DIAGRAM

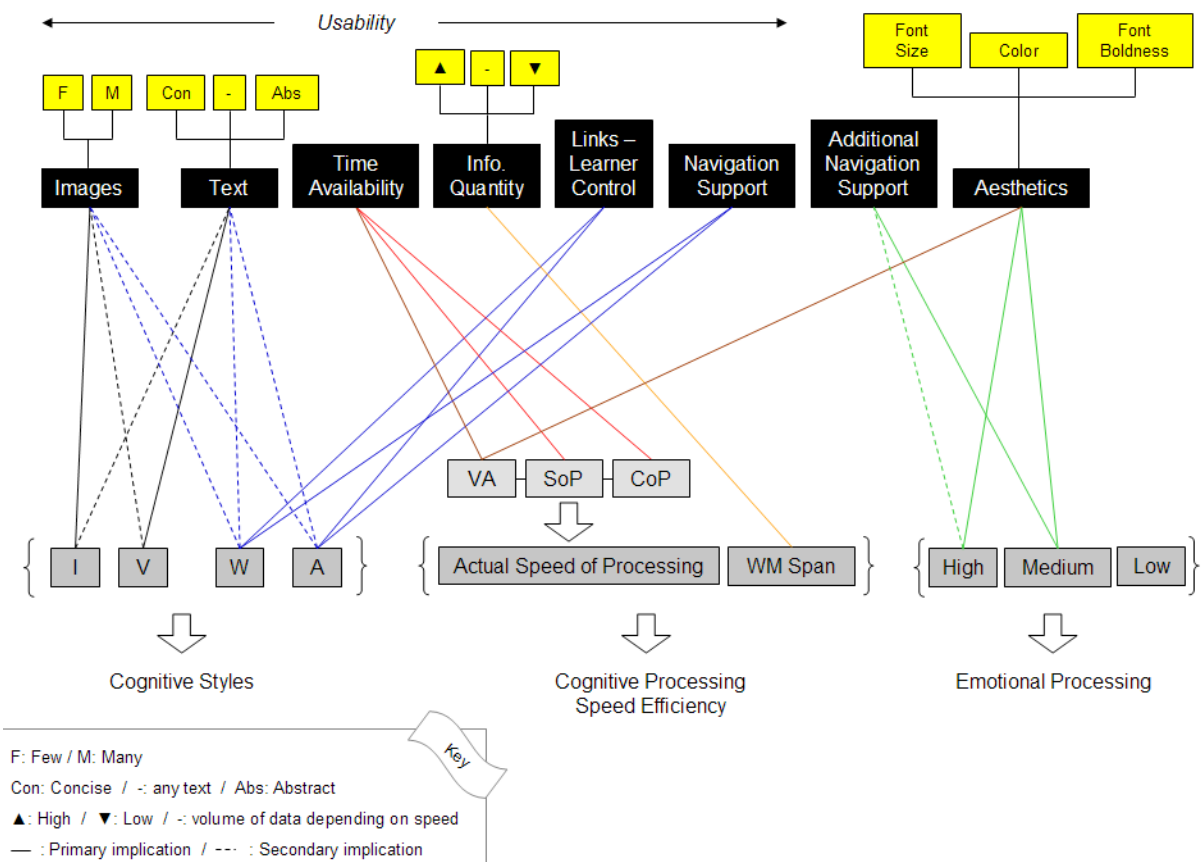
For a better understanding of the three dimensions' implications and their relation with the information space a diagram that presents a high level correlation of these implications with selected tags of the information space (a code used in Web languages to define a format change or hypertext link) is depicted in Figure 5. These tags (images, text, information quantity, links–learner control, navigation support, additional navigation support, and aesthetics) 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. Therefore, we include in the Cognitive 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 and navigation support tag, which in turn is secondary affected by high and medium emotional processing, while might secondary affect the number of images or kind of text to be displayed, consequently. Actual speed of processing parameters (visual attention, speed of processing, and control of processing) as well as working memory span are primarily affecting information quantity. Eventually, emotional processing is primarily affecting additional navigation support and aesthetics, as visual attention does, while secondary affects information quantity.

A practical example of the Data–Implications Correlation Diagram could be as follows, a user might be identified that is: Verbalizer (V)–Wholist (W) with regards to the Cognitive Style, has an Actual Cognitive Processing Speed Efficiency of 1000 msec, and a fair Working Memory Span (weighting 5/7), with regards to his/her Cognitive Processing Speed Efficiency, and (s)he has a High Emotional processing. The tags affected,

Figure 5. Data–implications correlation diagram



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 (less learner control because (s)he is Wholist), Additional Navigation Support (significant because (s)he has high emotional processing), and high aesthetics (to give more structured and well defined information, with more colors, larger fonts, more bold text, since (s)he has high emotional processing). At this point it should be mentioned that in case of internal correlation conflicts primary implications take over secondary ones. Additionally, since emotional processing 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.

OVERVIEWING AN ADAPTIVE WEB ARCHITECTURE AND THE COMPREHENSIVE USER PROFILE CONSTRUCTION

In this section, an adaptive Web-based environment is overviewed trying to convey the essence and the peculiarities encapsulated above and further indicate the construction of a Comprehensive User Profile. The current system, AdaptiveWeb[1] (see Figure 6–Germanakos et al., 2007b), is a Web-based and mobile Web application. It is detached into four parts, interrelated components, each one representing a stand alone Web system briefly presented below. The technology used to build each Web system is ASP .Net.

In order to get personalized and adapted content, a user has to create his/her comprehensive profile. Responsible for this part is the "User Profile Construction" component (see Figure 7).

Figure 6. AdaptiveWeb System Architecture

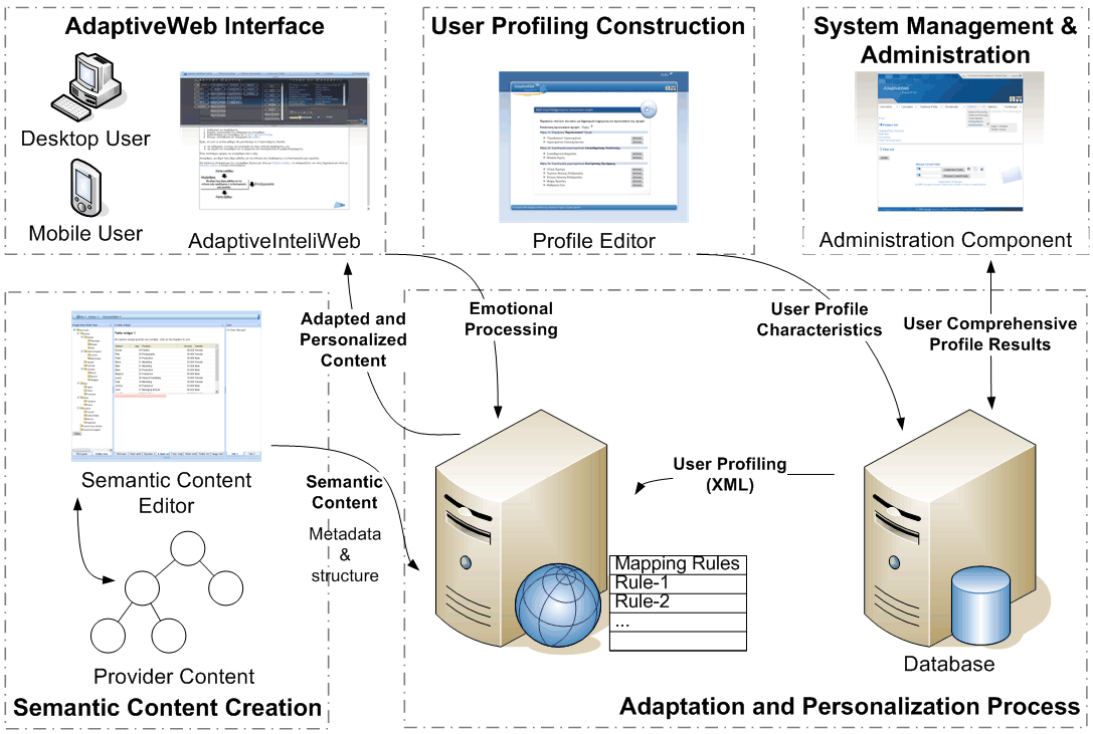
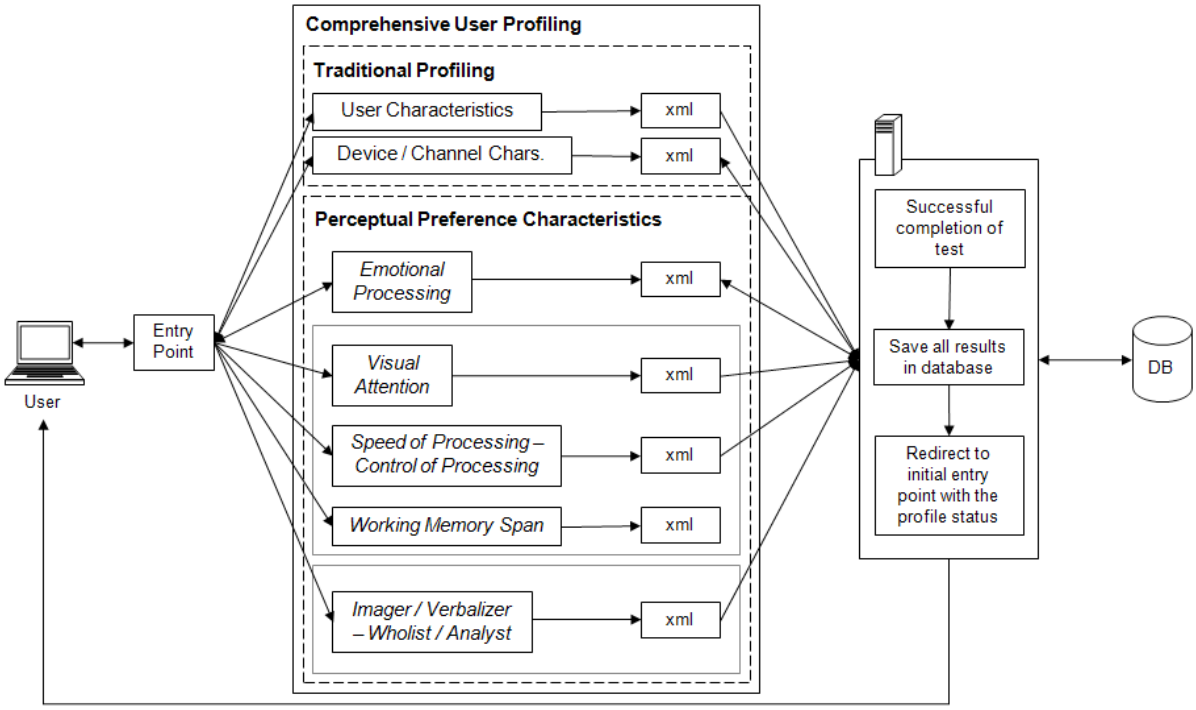


Figure 7. User profile construction

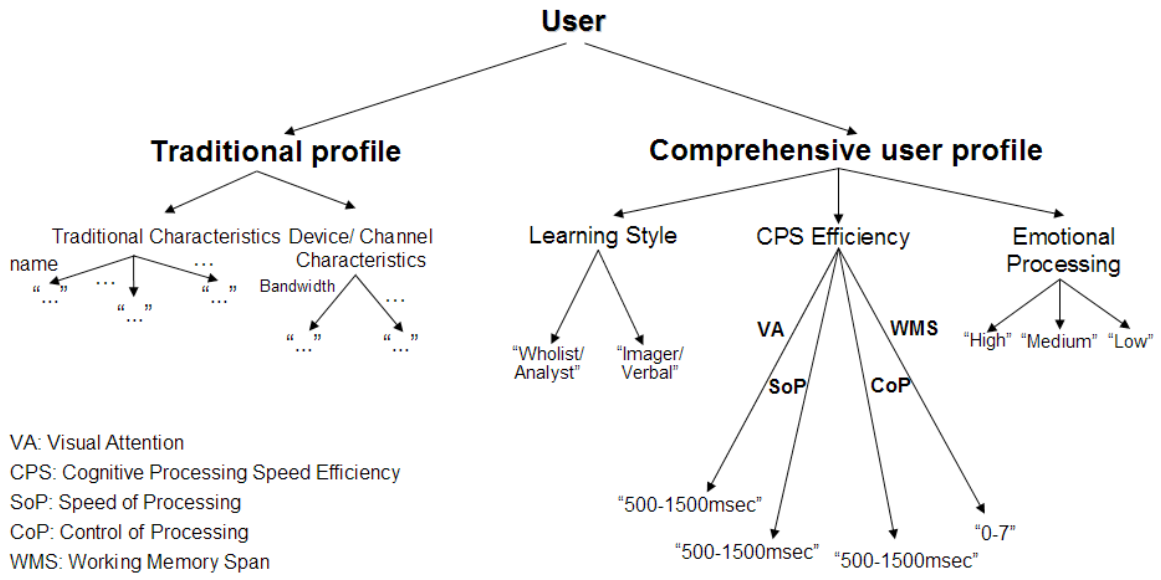


At this point the user has to give his/her "Traditional" and Device / Channel Characteristics and further complete a number of real-time tests as well as answer some questionnaires for identifying his/her Perceptual Preference Characteristics and consequently generating his/her cumulative profile. If a user has not completed all the tests available, the system will not be able to give him a Web-page reconstructed.

The second component is the system's "Semantic Content Editor", where the provider will build his/her Web site by defining the content as objects. The Web site structure has to be "well-formatted" and the objects have to be "well-defined" (based on given semantic tags) by the editor in order to give the best results to the end-user. The technology used for creating the personalized content is XML, which is a powerful and one of the most common markup languages nowadays, used for describing data and to focus on what data is. For a better insight, the Tree Structure of the Comprehensive User Profile, giving emphasis on the comprehensive user profile structure, is depicted in Figure 8. The author of the page uploads the content on the system's database, which will be mapped after with the system's "Mapping Rules". The system's "Mapping Rules" are functions that run on the AdaptiveWeb server and comprise the main body of the adaptation and personalization procedure of the provider's content, according to the user's comprehensive profile. In this section, all the system's components interact with each other in order to create and give personalized and adapted content to the end user.

The last component of the architecture is the "AdaptiveWeb Interface" which is a Web application used for displaying the raw or personalized and adapted content on the user's device. This can be a home desktop, laptop or a mobile device. Using this interface the user will navigate through the provider's content. At the very beginning the interface will show the raw, not personalized content of the provider. When the user wants to personalize and adapt the content according

Figure 8. The tree structure of the comprehensive user profile XML document



to his/her comprehensive profile he / she will proceed by giving his username and password. The corresponding profile will be loaded onto the server and in proportion with his/her cumulative characteristics the content of the provider will be mapped with the "Mapping Rules". The content will be adapted according to the user's preferences. The new, adapted content will then be loaded onto the user's device. While navigating, the user will be able to change his/her emotional state through a dynamic slide bar on the system's toolbar. By changing his/her current emotional state, the server will be alerted and the content will be "shaped" and changed according to his/her emotional state.

EXPERIMENTAL EVALUATION

In order to manipulate the parameters of an adaptive system according to user characteristics, the research has to go through the stage of extracting quantified elements that represent deeper psychological cognitive and emotional abilities. These extracted elements cannot be directly used in a Web environment, but a numerical equivalent can define the parameters that are to be used in a personalization system.

The current experiment is consisted of two distinct phases: phase I was conducted at the University of Cyprus, while phase II 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 the remaining parameters of our model (working memory, cognitive processing efficiency, emotional processing).

All participants were students from the Universities of Cyprus and Athens; phase I was conducted with a sample of 138 students, whilst phase II with 82 individuals. 35% of the participants were male and 65% were female, and their age varied

from 17 to 22 with a mean age of 19. The environment in which the procedure took place was an e-Learning course on algorithms. The course subject was chosen due to the fact that students of the departments where the experiment took place had absolutely no experience on 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 Perceptual Preferences, while the other half were taught in a mismatched way. We expected that users in the matched condition, both in phase I and phase II, would outperform those in the mismatched condition.

In order to evaluate the effect of matched and mismatched conditions, participants took an online assessment 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 online exam.

At this point, it should be clarified that matching and mismatching instructional style is a process with different implications for each dimension of our model (see Table 1).

Questionnaires

In this specific e-Learning setting, Users' Perceptual Preferences were the sole parameters that comprised each user profile, since demographics and device characteristics were controlled for. In order to build each user profile according to our model, we used a number of questionnaires that address all theories involved.

- **Cognitive Style:** Riding's Cognitive Style Analysis, standardized in Greek and integrated in .NET platform
- **Cognitive Processing Efficiency:** Speed and accuracy task-based tests that assess control of processing, speed of processing, visual attention and visuospatial working memory. Originally developed in the E-prime platform, we integrated them into the .NET platform.
- **Core (general) Anxiety:** Spielberger's State-Trait Anxiety Inventory (STAI)–10 items (Only the trait scale was used) (Spielberger, 1983).
- **Application Specific Anxiety:** Cassady's Cognitive Test Anxiety scale–27 items (Cassady & Johnson, 2002).

Table 1. Implications for matched/mismatched conditions

	Cognitive Style	Working Memory	**Cognitive Processing Speed Efficiency**	***Emotional Processing***
Matched Condition	Presentation and structure of information matches user's preference	Low Working Memory users are provided with segmented information	Each user has in his disposal the amount of time that fits his ability	*Users with moderate and high levels of anxiety receive aesthetic enhancement of the content and navigational help*
Mismatched Condition	*Presentation and structure of information does not coincide with user's preference*	*Low Working Memory users are provided with the whole information*	*Users' with low speed of processing have less time in their disposal (the same with "medium" users).*	*Users with moderate and high levels of anxiety receive no additional help or aesthetics*

- **Current Anxiety:** Self-reported measures of state anxiety taken during the assessment phase of the experiment, in time slots of every 10 minutes–6 Time slots.
- **Emotion Regulation:** This questionnaire was developed by us; cronbach's α that indicates scale reliability reaches 0.718.

Results

As expected, in both experiments the matched condition group outperformed those of the mismatched group. Figure 9 displays the aggregated differences in performance (the dependent variable of exam score), in matched and mismatched conditions.

Table 2 shows the differences of means (one way ANOVA) and their statistical significance for the parameters of Cognitive Style, Cognitive Efficiency Speed, and Emotional Processing.

The relatively small sample that falls into each category and its distribution hamper statistical analysis of the working memory (WM) parameter. In any case, the difference between those with high WM and those with low WM, when both categories receive non-segmented (whole) content, approaches statistical significance: 57.06% for those with High WM, 47.37% for those with Low WM, Welch statistic= 3.988, p=0.054.

This demonstrates that WM has indeed some effect on an e-Learning environment. Moreover, if those with low WM receive segmented information, then the difference of means decreases and becomes non-significant (57.06% for High WM, 54.90% for those with Low WM, Welch statistic=0.165, p=0.687).

In the case of Emotional Processing, the results of experiments conducted within the actual learning environment, as we hypothesized, show that users with high or medium anxiety level, lacking the moderating role of emotion regulation, are in a greater need of enhancing the aesthetic aspects of our system and the provision of additional help, in order to perform as well as low anxiety users. Users with low anxiety levels focus more on usability aspects.

We can observe in Table 3 that all types of anxiety are positively correlated with each other and are negatively correlated with emotion regulation. These findings support our hypothesis and it can be argued that our theory concerning the relationship between anxiety and regulation has a logical meaning.

In Tables 4 and 5 we can see an even stronger relationship between emotion regulation and core and specific anxiety respectively. A statistically significant analysis of variance for each anxiety type shows that if we categorize the participants according to their emotional regulation ability, then the anxiety means vary significantly with the high regulation group scoring much higher than the low one.

Finally, in Table 6 we can see that the two conditions (matched aesthetics/mismatched aesthetics) are differentiating the sample significantly always in relation with performance. Participants in the matched category scored higher than the ones in the mismatched and additionally lower anxious (core or specific or both) scored higher than high anxious, always of course in relation to match/mismatch factor.

We also found that participants with low application specific anxiety perform better than participants with high specific anxiety in both matched and mismatched environments. Additionally, in categories that a certain amount of anxiety exists, match-mismatch factor is extremely important for user performance. Participants with matched environments scored highly while participants with mismatched environments had poor performance. Emotion regulation is negatively correlated with current anxiety. High emotion regulation means low current anxiety and low emotion regulation means high current anxiety. Finally, current anxiety is indicative of performance. High current anxiety means test scores below average while low current anxiety means high scores.

Figure 9. Aggregated differences in matched/mismatch condition

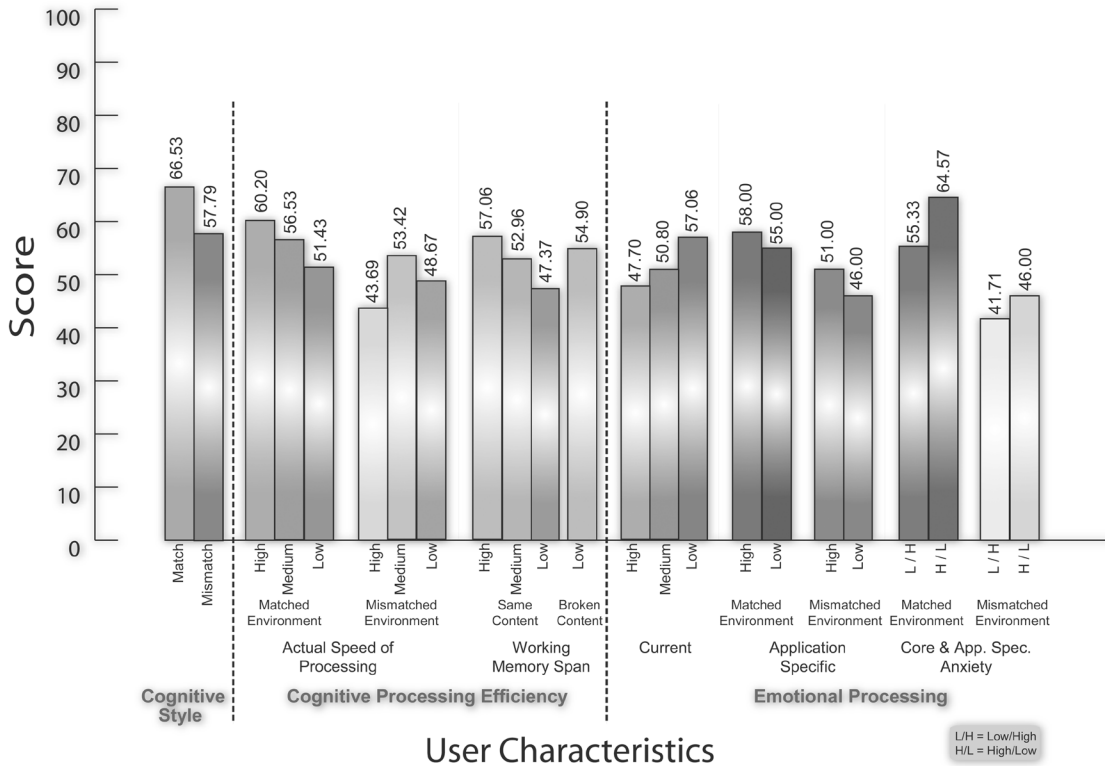


Table 2. Differences of means in the matched/mismatched condition for cognitive style and cognitive efficiency speed

	Match Score	Match n	Mismatch Score	Mismatch n	F	Sig.
Cognitive Style	66.53%	53	57.79%	61	6.330	0.013
Cognitive Processing Speed Efficiency	57.00%	41	48.93%	41	5.345	0.023

Table 3. Correlations of types of anxiety and emotion regulation

	Core Anxiety	**Application Specific Anxiety**	**Current Anxiety**	**Emotion Regulation**
Core Anxiety	1	.613(**)	.288(**)	-.569(**)
Application Specific Anxiety	.613(**)	1	.501(**)	-.471(**)
Current Anxiety	.288(**)	.501(**)	1	-.094
Emotion Regulation	-.569(**)	-.471(**)	-.094	1

** *Correlation is significant at the 0.01 level (2-tailed).*

Table 4. Analysis of variance between emotion regulation groups and core anxiety means

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.316	2	2.158	18.554	.000
Within Groups	10.700	92	.116		
Total	15.015	94			

Table 5. Analysis of variance between emotion regulation groups and specific anxiety means

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.345	2	4.173	15.226	.000
Within Groups	25.213	92	.274		
Total	33.558	94			

Table 6. Multifactorial ANOVA (factors-core anxiety, application specific anxiety and aesthetics)

Source	Type III Sum of Squares (a)	df	Mean Square	F	Sig.
MatchedAesthetics	1097.361	1	1097.361	4.238	.043
core_groups * specific_ groups * MatchedAesthetics	983.259	1	983.259	3.797	.055

Dependent Variable: Score %
(a) *R Squared = .102 (Adjusted R Squared = .017)*

DISCUSSION AND CONCLUSIONS

Adaptive Hypermedia and Web personalization are two distinct well established areas of research both investigating methods and techniques to move conventional static systems beyond traditional borders to more intelligent, adaptive and personalized implementations. They share a common goal: to alleviate navigational difficulties and satisfy the heterogeneous needs of the user population by adapting according to user specific characteristics. In order to do that, the user profile construction is considered necessary.

The basic objective of this chapter was to make an extensive reference of a combination of concepts and techniques coming from different research areas, Adaptive Hypermedia and Web personalization, 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 profile, under a common filtering element (User Perceptual Preference Characteristics), supporting the provision of the most apt and optimized user-centred Web-based result.

The proposed three-dimensional model (based on which the AdaptiveWeb system has been developed) seems to cover a wide area of human factors that are proven significant in computer mediated learning procedures, and may provide a basis for meaningful adaptation and personalization.

The current results of the evaluation, conducted in an e-Learning environment, show that it is possible to increase academic performance by taking into account cognitive and emotional parameters within the context of Web-based learning. Re-

search in Adaptive Hypermedia often focuses on a single aspect of individual differences (such as cognitive style), resulting in limited effects on academic performance. However, the combination of multiple individual differences and emotional parameters in a comprehensive user model may promote effective learning, regardless of specific users' preferences and abilities, ensuring the success of e-Learning environments.

Also, the proposed model seems to cover a wide area of human factors that are proven significant in computer mediated learning procedures, and may provide a basis for meaningful personalization. Cognitive style is certainly of high importance, cognitive processing efficiency and Working Memory have an impact on the Web environment, and anxiety (as the main component of Emotional Processing) can be manipulated for optimization of performance. We believe that combining the level of anxiety of an individual with the moderating role of Emotion Regulation, it is possible to clarify, at some extent, how emotional responses of the individual hamper or promote learning procedures. Thus, by personalizing Web-based content, taking into account emotional processing, we can avoid stressful instances and take full advantage of his/her cognitive capacity at any time.

There are of course limitations in our approach, mainly due to the nature of the Web content that often limits radically differentiated adaptation, and the psychometric challenges of measuring a wide spectrum of human cognition and emotionality. The relationship between different dimensions of the model must be further investigated, and an experiment focused on the effect of working memory must be conducted.

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FUTURE RESEARCH DIRECTIONS

The initial evaluative results were really encouraging for the future of the current work since it has been identified that in many cases there is high positive correlation of matched conditions with performance, as well as between the dimensions of the various factors of the proposed model. This fact demonstrates the effectiveness of incorporating human factors in Web-based personalized environments. Synoptically, this holistic approach to information processing and learning in Web-based environments will lead to the formulation of adaptation rules, personalization techniques, designing principles, assessment methods, new practices, effective semantically enriched educational content, affective system responses and generally the enhancement of hypermedia with exceptionally important human cognitive and emotional factor.

Future and emerging trends include the further investigation of constraints and challenges arise from the implementation of such issues on mobile devices and channels; study on 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 a comprehensive user profile; the incorporation of physiological measurements of emotions and anxiety in such a model, with the use of biometrical sensors; as well as the use of an eye-tracker tool to clarify the role of Visual Attention in Web-based communication environments.

Our future work will embrace all the above-mentioned future research opportunities and directions aiming to develop a system that will provide a complete adaptation and personalization Web-based solution to the users satisfying their individual needs and preferences.

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ENDNOTES

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