Embracing Cognitive Factors and Fuzzy Logic in Adaptive Interactive Systems

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Abstract: The increased demand of services on the Web to satisfy the diverse characteristics of users have resulted in a plethora of applications that aim to provide personalized services based on the heterogeneous needs and preferences of users. With the aim to enhance and support the personalization process of Web applications, an innovative adaptation framework is proposed embracing cognitive factors of users which serve as the user model, and Computational Intelligence techniques that decide on the adaptation effects of Web applications for providing a personalized user experience. The user model is based on a series of psychometric measures which capture particular cognitive factors of users, and the adaptation mechanism includes the utilization of Artificial Neural Networks and Fuzzy Logic for exploiting the benefits of intelligent classification and partial truth in the adaptation process. The proposed method has been evaluated with a user study that has revealed a main effect of cognitive factors of users on the adaptation of Web content and functionality since users were more efficient and effective in completing tasks in the adapted than the non-adapted version of the same environment.

Keywords: User Modeling, Adaptation, Personalization, Cognitive Styles, Artificial Neural Networks, Fuzzy Logic

1. Introduction

Adaptive interactive systems have attracted many researchers' and practitioners' interest from different communities since the mid-1990s due to the exponential increase of content and usage of the World Wide Web [1, 2]. These researchers and practitioners

primarily originate from communities such as, hypermedia, user modeling, machine learning, information retrieval, web mining, cognitive sciences, and Web-based education. Given that traditional static interactive Web-based systems treat all users the same way, being unable to satisfy the heterogeneous needs and preferences of users [1, 2], the main purpose of adaptive interactive systems is to provide an alternative to the "one size fits all" approach of such static user interfaces by adapting the systems' content and functionality based on the users' needs and preferences. The ultimate outcome of this adaptation is to improve the systems' usability and provide a positive user experience. To better explain this through an example, an adaptive electronic encyclopedia could offer different functionality and content based on the readers' knowledge and interests, while an adaptive e-commerce Web-site could provide a personalized product catalogue and tools to customers with different needs and preferences.

In this context, the high-level research goals of adaptive interactive systems are focused around two main issues; appropriate user modeling, dealing with what information is important about the user for deciding upon the different adaptation effects, and suitable adaptation procedures, dealing with what adaptation types and mechanisms are most effective to be performed and how they can be translated into adaptive user interface designs, in order to improve the systems' usability and provide a positive user experience.

The work presented in this paper lies on previous research [3, 4, 5, 6] which has shown that specific cognitive factors may have significant impact in the adaptation and personalization process of adaptive interactive systems. Specifically, previous work [3, 6] indicated that since content can be either presented visually or verbally and functionality of Web applications can be altered according to the users' specific navigation behavior, e.g., linear or nonlinear navigation behavior, cognitive styles of users [7], which describe the way individuals perceive and organize information, might be applied effectively for designing adaptive Web applications. The main outcome from the previous work conducted has shown that the adapted version of a Web environment based on users' cognitive factors can increase their satisfaction, task accuracy and performance [3]. Since prior work initially aimed to understand the theoretical implications of cognitive factors on the adaptation of Web environments in terms of usability and user experience, it had

utilized a simple and deterministic rule-based mechanism and provided predefined environments for each type of cognitive style.

Follow up work of the authors is the current work, to support the whole adaptation process for personalizing content and functionality of interactive systems to the specific cognitive characteristics of users through a complete adaptation mechanism embracing: i) explicit and implicit user modeling techniques for eliciting the cognitive characteristics of users, ii) an authoring tool for supporting Web authors throughout the content creation, and iii) an intelligent adaptation mechanism for dynamically reconstructing content and functionality based on Computational Intelligence techniques, such as Artificial Neural Networks and Fuzzy Logic. The overarching aim of this work is to study the effect of adapting content and functionality of Web applications based on cognitive factors of users. While the work in [3] of the authors utilized a deterministic rule-based adaptation mechanism to provide the adaptation effects based on cognitive characteristics of users, the difference of this work is to extend the adaptation mechanism and exploit the benefits of partial truth by employing the use of Fuzzy Logic in the adaptation process, and investigate whether it increases usability and user experience of adapted Web applications compared to non-adapted ones.

The paper is organized as follows: In Section 2, we provide an overview of adaptive interactive systems focusing on the adaptation effects and mechanisms. Section 3 presents the proposed adaptation mechanism which is evaluated with a user study in Section 4. Consequently, we conclude the paper and describe our directions of future work in Section 5.

2. User Adaptation in Interactive Systems

This section is focused on the adaptation side of adaptive interactive systems. Specifically, we focus our analysis on identifying which visible aspects of the user interface should be adapted and how, what adaptation mechanisms should be implemented, and how to communicate these adaptation effects to the user interface.

2.1 Adaptation Effects

An important issue in adaptive interactive systems is which visible features of the system can be adapted by a particular technique. A number of ways exist to adapt hypermedia content and functionality [2]. These are classified under two main classes of adaptation technologies; content-level adaptation, called *adaptive presentation* [8], and link-level adaptation, called *adaptive navigation support* [11]. Adaptive presentation relates to the adaptation of hypermedia elements inside nodes, and adaptive navigation support relates to the adaptation of links inside nodes. We shall refer to the notion of "nodes" throughout the following sections to refer to Web-pages that contain hypermedia content and hyperlinks connected to other nodes (other Web-pages).

Adaptive presentation relates to the adaptation of hypermedia elements inside nodes. The idea behind adaptive presentation is to adapt the information elements (or the content) inside a node accessed by a particular user to the needs and preferences of that user. Adapting the presentation of content within a node is most often performed as a manipulation of fragments [9, 10]. Such manipulations aim to provide prerequisite, additional or comparative explanations. For example, additional information can be shown for users with a specific state of knowledge to provide missing prerequisite knowledge, additional details, or a comparison with a previously known concept. Techniques that are used to provide adaptive presentation include: i) inserting/removing fragments that are relevant to the user, ii) expanding/collapsing content fragments (e.g., expanding additional explanations to novice users), iii) altering content fragments (e.g., presenting a diagrammatical representation of a concept to an Imager cognitive style user [3]), and iv) sorting content fragments (e.g., some users may prefer to see an example before a definition, while others might prefer the exact opposite).

Figure 1 illustrates an example of content adaptation as utilized in [3] where users with different cognitive typologies (i.e., Verbal, Imager) were provided with different content fragment variations, i.e., users belonging to the Verbal class (that process textual content more efficiently) were presented with more textual than graphical content, whereas users belonging to the Imager class (that process graphical content more efficiently) were presented with more graphical than textual content. Furthermore, the same study provided adaptive navigation support based on other cognitive factors (i.e.,

Wholist, Analyst) that seem to have an effect on the navigation behavior of users in interactive systems.

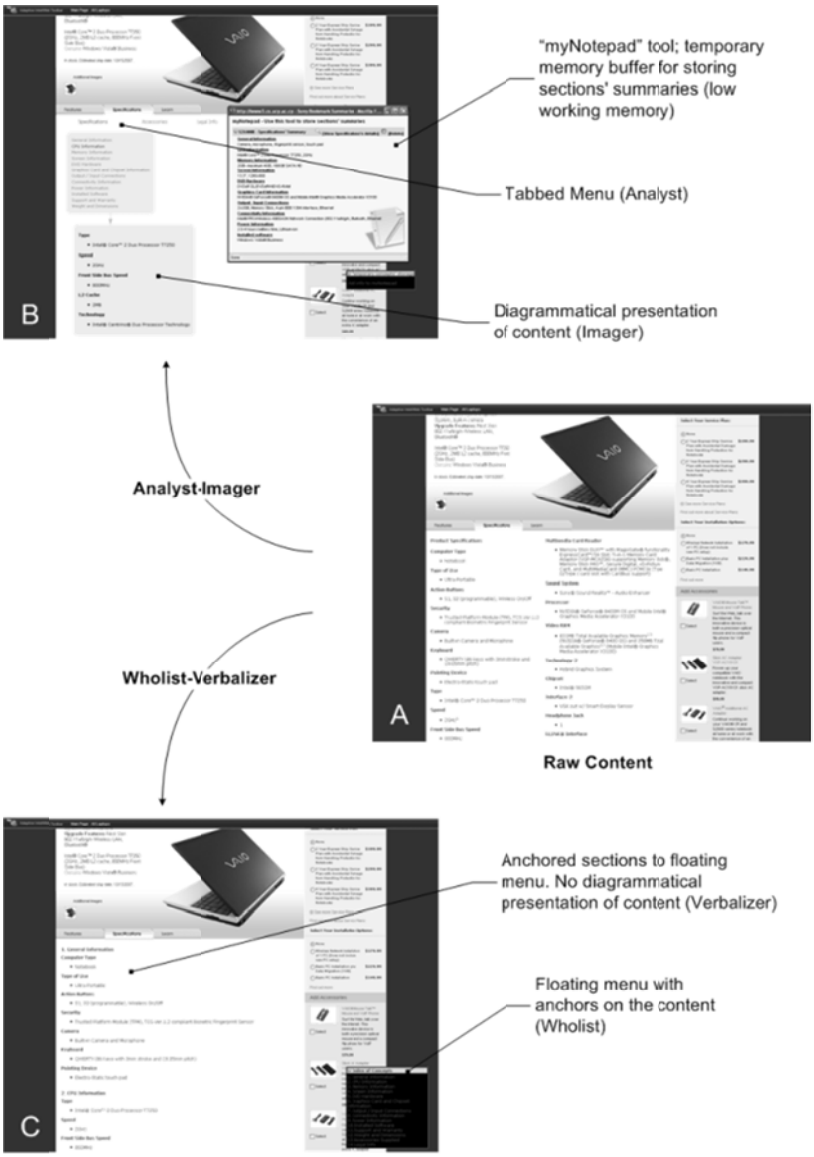

Figure 1. Content Adaptation based on Cognitive Styles of Users

Adaptive navigation support relates to the adaptation of links inside nodes. This kind of adaptation supports user navigation in an interactive system, by adapting to the goals, preferences, knowledge or the context of use of the individual user [11, 12]. The core idea behind this kind of adaptation is to adapt the presentation of hyperlinks/functionality within a node. Adaptive navigation support can be achieved by:

i) guiding the user in the system by suggesting the "next best" node to visit according to the user's goals, preferences and knowledge, ii) prioritizing links that are relevant to the user's interests or preferences closer to the top, iii) hiding, removing or disabling links to prohibit navigation space to irrelevant nodes, iv) augmenting links with additional information about the node behind the link, with some form of annotation, and v) dynamically generating new, non-authored links based on the user's interests and/or current context (i.e., location) in the system. For example, a location-based adaptive interactive system could recommend users with dynamic links of restaurants that are nearer to the users' current location and preferences.

2.2 Adaptation Mechanisms

Adaptation mechanisms apply specific algorithms that decide what adaptation will be performed on the content and functionality of the system. Various approaches have been proposed in the literature, including among others user customization, rule-based, content-based, collaborative-based and fuzzy-based mechanisms.

User customization provides a mechanism that allows users to construct a custom interface representation based on their own preferences. Once the user has entered this information, a matching process is used to find items that meet the specified criteria and displays them to the user. The system in this case is not considered adaptive, but rather adaptable, because it is explicitly decided by the user on how to adapt (configure) its content and functionality.

Rule-based mechanisms refer to the process of producing high-level information from a set of low-level metrics, related to both static and dynamic user context information. Bearing in mind that the dynamic part of the context data model can be updated in real time, it becomes obvious that the reasoning capabilities supported provide an added value in supporting users in the different tasks they are performing. Such rules can initiate automated system actions or compare predictive user interaction models with actual user interaction data gathered in real time, providing thus valuable insights related to the current user goals and efficiency of interactions. For example, an online banking system may contain a rule as follows: "*IF* [USER].logged = False AND [USER].loginattempts.count > 2 *THEN* [UIOBJECT].LiveSupport.show = True", which

indicates that the system should automatically offer a live customer support option to users who could not succeed to login in the system after trying to login for more than two times. A detailed analysis and comparison of rule-based mechanisms can be found in [13].

Content-based mechanisms make recommendations by analyzing the content of text-based information to identify items that are of particular interest to a user. A typical content-based mechanism includes the following steps: i) pre-fetch the content behind the links of the current page, ii) parse the pre-fetched pages to create a weighted keyword vector of each page, iii) compare the weighted keyword vector of each page with the user's preferences, that are also usually represented using a weighted keyword vector (e.g., based on TF.IDF term-weighting model [14]), and iv) suggest pages whose keyword vectors are the same with the user's preferences (e.g., based on vector similarities, using the Cosine similarity measure, or based on probabilistic approaches such as Bayesian classification). A detailed analysis and comparison of content-based mechanisms can be found in [15].

Collaborative mechanisms exploit the social process of people recommending something to other people they have been experienced with (e.g., read a book, watched a movie). Collaborative mechanisms are based on the assumption that if users X and Y rate n items similarly, or have similar behaviors (e.g., buying or watching), they will probably also have similar interests. Adaptive interactive systems utilize collaborative mechanisms to provide navigation support by recommending links of interest to users based on earlier expressed ratings or navigation behaviour of other similar to them users. A recent survey of collaborative mechanisms can be found in [16].

Fuzzy-based mechanisms mimic human decision-making and define a framework in which the inherent ambiguity of real information can be captured, modeled and used to reason under uncertainty [17]. Such mechanisms are based on the notions of Fuzzy Logic [18], which allows membership functions (fuzzy set theory) or truth values (fuzzy logic) to take values between 0 and 1, with 0 being absolute false and 1 absolute true. Fuzzy-based mechanisms are primarily combined with traditional machine learning techniques in order to produce behavior models with the aim to capture and manage the uncertainty of human behavior (e.g., Fuzzy Clustering, Fuzzy Association Rules and Fuzzy Bayesian

Networks) [17]. Other approaches utilize Fuzzy Logic inference to implement the personalization engine, where the user models are captured through traditional machine learning techniques. Fuzzy Logic inference systems are primarily performed by: i) fuzzifying the input data, ii) conducting fuzzy inference on the fuzzified data, and iii) defuzzifying the decisions to produce the final outcome.

Prior research works have applied Fuzzy Logic to address a variety of problems of adaptive interactive systems. Web recommendation systems utilized Fuzzy Logic for the representation of user profiles [19, 20, 21, 22, 23]. Educational adaptive hypermedia systems employed Fuzzy Logic for modeling users' knowledge of a particular domain [24, 25, 26, 27, 28]. Other related works include, [29] that proposed a generic Fuzzy-based model with the aim to capture imprecise interactions of users with interactive systems, [30] that proposed a Fuzzy-based linguistic model for adaptation based on cognitive and learning styles with the aim to assist the design of adaptive user interfaces with more natural language expressions, [31] that utilized Fuzzy Concept Networks for personalizing search results, and [32] that proposed a Fuzzy-based approach for personalizing geographic-based information.

In the same context, given that existing works have shown that Fuzzy Logic can support the personalization process of interactive systems by exploiting the benefits of human reasoning and partial truth, this work proposes a complete adaptation framework that embraces a Fuzzy-based adaptation mechanism utilizing Computational Intelligence techniques to combine the benefits of fuzziness and adaptation mechanisms for both content and functionality of Web environments using cognitive factors of users. An Artificial Neural Network is used initially to cluster users of similar type in specific categories and then, Fuzzy Logic replaces the use of deterministic truth in traditional adaptation rules, like the ones utilized in [3]. The main advantage of the technique is that users are considered to belong in more than one clusters (using fuzzy memberships) and the reasoning of the adaptation follows a fuzzy approach which is closer to the real decision making process humans follow.

3. Proposed Fuzzy-based Adaptation Framework

In this section we describe the fuzzy-based adaptation framework (Figure 2) which has the aim to provide adapted content and functionality of Web environments based on cognitive factors of users.

The framework consists of the following interconnected layers: i) User Modeling, for extracting the cognitive characteristics of users, ii) Semantic Authoring Tool, for the creation of semantically-enriched, machine-understandable content (as proposed in [33]), iii) Fuzzy Adaptation Mechanism, that performs various adaptation rules obtained by experts and which are based on the user models and the semantically-enriched content, and iv) Adaptive User Interface, that presents the Web content in an adapted format and through adapted navigation controls based on the users' cognitive characteristics.

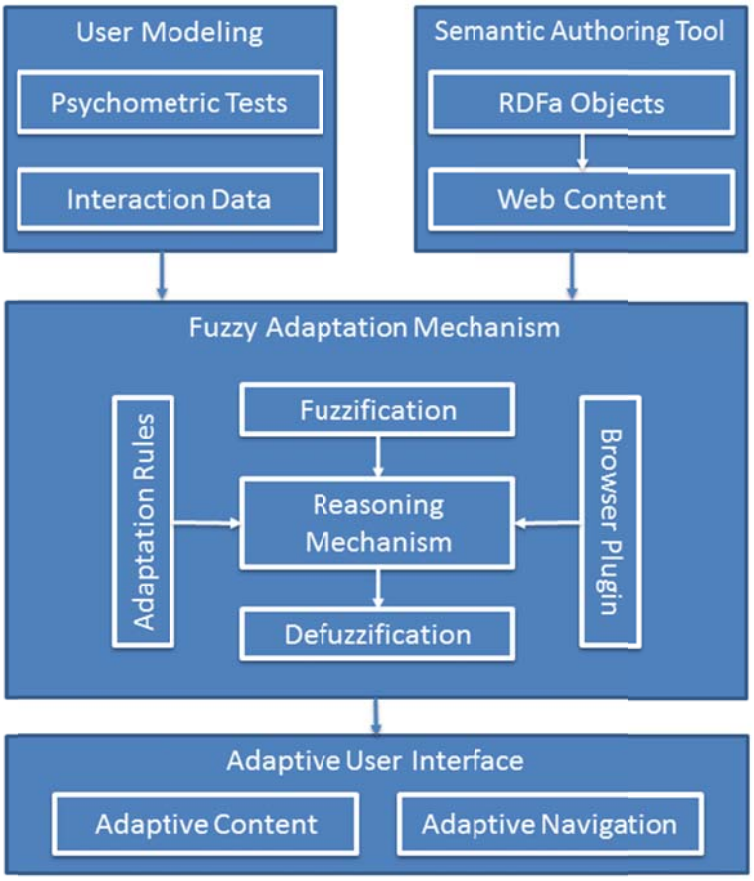

Figure 2. Fuzzy Adaptation Framework

3.1 User Modeling

For the user modeling a series of psychometric tests are used to highlight differences in the cognitive characteristics of users, and, in combination with the use of an Artificial Neural Network that analyzes the interaction data of users, the fuzzy membership degrees of the users belonging to specific classes are obtained. Among the popular theories of individual styles proposed [7, 34, 35, 36, 37, 38], the current work utilizes Riding's Cognitive Style Analysis (CSA) [7, 38] and Baddeley's Working Memory Span (WMS) [39, 40] which are discussed next.

Cognitive Styles. Riding's CSA consists of two dimensions; the Verbal/Imager dimension refers to how individuals process information, and the Wholist/Analyst dimension refers to how individuals organize information [7, 38]. The Verbal/Imager dimension consists of three classes, users that belong to the Verbal, IntermediateV/I or Imager class. Users that belong to the Verbal class can proportionally process textual and/or auditory content more efficiently than images, whereas users that belong to the Imager class the opposite. Users that belong in between the two end points (i.e., IntermediateV/I) do not differ significantly with regards to information processing. The Wholist/Analyst dimension consists of three classes, users that belong to the Wholist, IntermediateW/A or Analyst class. Specifically, users that belong to the Wholist class view a situation and organize information as a whole and are supposed to take a linear approach in hypermedia navigation. Users that belong to the Analyst class view a situation as a collection of parts, stress one or two aspects at a time and are supposed to take a nonlinear approach in hypermedia navigation. Users that belong in between the two end points of the Wholist/Analyst scale (i.e., IntermediateW/A) do not differ significantly with regards to information organization.

In this context, Riding has proposed a psychometric test [7] for eliciting the users' cognitive styles that comprises of two sub-tests that respectively indicate the position of an individual on each of the Wholist/Analyst and Verbal/Imager dimensions by means of a ratio.

The first sub-test assesses the Wholist/Analyst dimension by presenting a series of 40 questions on judging and comparing geometrical figures made up of three basic

geometric shapes (i.e., square, rectangle, and triangle). 20 of these questions require the participants to compare whether a pair of figures are identical or not (e.g., "Is shape X the same as shape Y?"), and the rest 20 questions require the participants to judge whether a single figure is part of another complex figure ("Is shape X contained in shape Y?"). Half of the items have either the same shape or have the shape embedded in the more complex figure and half of the shapes do not. The test records the response time of each given answer to the questions and then uses a three-phase algorithm to determine the participant's cognitive style. The algorithm performs the following steps: i) calculate the average response time on each section (20 questions in each section) of the CSA test, ii) calculate the ratio between the average response times on each section's stimuli (wholist and analytic), and iii) associate the value of each subject's Wholist/Analyst ratio with a style category. A low ratio (<=1.02) classifies the participant as a "Wholist", a high ratio (>1.35) classifies the participant as an "Analyst", while a ratio in between the two end points classifies the participant as an "IntermediateW/A" [7].

The second sub-test assesses the Verbal/Imager dimension by presenting a series of 48 questions about conceptual category and appearance (i.e., color) to be judged by the participants true or false. 24 statements require the participants to compare two objects conceptually (e.g., "Are ski and cricket the same type?"), and 24 statements require the participants to compare the color of two objects (e.g., "Are cream and paper the same color?"). As in the Wholist/Analyst sub-test, the psychometric test records the response time of each given answer to the questions and then uses a three-phase algorithm to determine the participant's cognitive style. The algorithm performs the following steps: i) calculate the average response time on each section (24 questions in each section) of the CSA test, ii) calculate the ratio between the average response times on the verbal (conceptual category) and imagery (appearance) stimuli, and iii) associate the value of each subject's Verbal/Imager ratio with a style category. A low ratio (≤0.98) classifies the participant as a "Verbal", a high ratio (>1.09) classifies the participant as an "Imager", while a ratio in between the two end points classifies the participant as an "IntermediateV/I" [7].

To this end, we consider that Riding's CSA implications can be mapped on Web environments, since they consist of distinct scales that respond directly to different

aspects of the Web space. The CSA could be considered as an inclusive theoretical model, since it is derived from the common axis of a number of theories [38] and can provide clear guidelines in the context of Web design (i.e., selecting to present visual/verbal content and structuring information flow in a wholistic/analytic manner).

Working Memory Span. "The term working memory refers to a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" [39, 40]. Baddeley also refers to individual differences in the Working Memory Span (WMS) of the population and many other studies support that working memory capacity varies among people and predicts individual differences in intellectual ability [41, 42], thus providing a very good argument for using this concept as a personalization factor. Each corresponding WMS instance (i.e., low/medium/high), indicates the working memory capacity of a person (e.g., a person with low WMS has low working memory capacity and so on). Enhanced working memory increases the connections and associations that can be built either between the items of the newly encountered information or between this information and information already stored in the long-term memory. Also, various research works [39-43] argue that working memory has an effect on comprehension, learning and problem solving. It is mainly used in mental tasks, such as arithmetic tasks, remembering a number in a multiplication problem and adding that number later on, or creating a new password and using that password later for authentication.

The user modeling component utilizes two tasks for addressing storage capacity in short-term memory, a verbal and a visual test based on Baddeley's multicomponent model of working memory [39, 40], whose results are combined to indicate user's working memory capacity.

The verbal test shows a series of statements and requires the participants to respond whether they are true or false. In addition, users are required to remember and write later down the last word of each sentence. The test includes 6 levels of difficulty, e.g., in level 3, users are required to respond with "true/false" to three successive sentences and also need to remember and provide the last word of each sentence. For example, for the sentences "Knives are sharp", "The sun is shining", and "Fish have fur"

the user should respectively respond true, true and false, and then provide the words "sharp", "shining" and "fur" to the system. As the test proceeds and the user provides the correct answers the level increases and in the end this level is associated with the users' working memory capacity.

The visual test illustrates a geometric figure on the screen and the user is required to memorize the figure. Thereafter, the figure disappears and 5 similar figures are illustrated on the screen, numbered from 1 to 5. The user is required to provide the number (utilizing the keyboard) of the corresponding figure that is the same as the initial figure. The test consists of 21 figures (seven levels of three trials each). As the user correctly identifies the figures of each trial, the test provides more complex figures and as the level increases it indicates enhanced working memory capacity for that user.

Intelligent Clustering. Artificial Neural Networks (ANNs) [44] were developed and used in this work to classify users in specific categories of cognitive style based on the results of the psychometric tests (i.e., assign users to categories based on the cognitive dimensions explained above). The mechanism accordingly calculates the membership degree of each user in each group of cognitive typology. Thus, users belong at the same time to more than one group but with respect to a specific degree (introducing the notion of fuzziness). In contrast to using the original Riding CSA test values, where classification (hard clustering) is used to divide users into distinct groups, in fuzzy clustering (or soft clustering using ANNs) users belong to more than one group [45]. The users' respective membership degree or level informs us on the strength of the association between the users and categories representing the cognitive typology dimension.

In particular, in this work, the ANNs developed were pattern recognition feedforward networks [44] with one input, one hidden and one output layer. Initially, the data were randomly split into three subsets, the training, the validation and the testing subset consisting of 60%, 20% and 20% of the original data samples. The inputs (ratios of Riding's CSA test) were inserted in the computational neurons and the output (the membership degree of each user in cognitive typologies measured in percentage) was calculated. The rest parameters of the ANNs developed are: the number of neurons in the

hidden layer varied from 2-20 neurons, the transfer function was the hyperbolic tangent sigmoid (*tansig*), the training function was the Levenberg-Marquardt backpropagation (*trainlm*), the number of epochs was set to 500, the backpropagation weight/bias learning function was the Gradient descent with momentum backpropagation (*learngdm*) and the performance function of the network was based on the weight sum of two factors: the mean squared error and the mean squared weight and bias values (*msereg*).

3.2 Semantic Authoring Tool

A semantic authoring tool was developed as described in [32] that supported the creation of adaptive Web content with semantic markups. The development was based on Wordpress [46], which is an open widely used Content Management System on the World Wide Web. In particular, a customized version of Wordpress has been developed and extended to enable the creation process of Web content with specific RDFa tags to serve semantic annotations. The RDFa standard was used in this work since it easily integrates machine-understandable information into the current Web-page paradigm and workflow [47].

An RDFa schema [48] was designed for that purpose to enable standard annotations in an XHTML Web-page, thus making structured data available for our framework's adaptation mechanism, but also for any service or tool that supports the same standard. Table 1 shows an instance of the RDFa content model.

Table 1. RDFa Instance of a Web Object

```
<div typeof="v:SmartObject">
    <span property="v: name">PC Specifications</span>
    <div property="v:element">
        <span property="v:title">Storage</span>
        <span property="v:content">250GB HD</span>
    </div>
    <div property="v:element">
        <span property="v:title">CPU</span>
        <span property="v:content">2GHz CPU I5</span>
    </div>
</div>
```

The RDFa instance described in Table 1 consists of a number of classes and properties for an adaptive Web object. The main class of the RDFa vocabulary is the

SmartObject representing an adaptive Web object. This class has the following properties: i) *name*, the concept's name, ii) *element*, the element of a concept, iii) *title*, the title of the concept's element, and iv) content, the content of the concept's element.

Particularly, the Web authoring tool has been extended to include actions that enable content annotations based on the RDFa schema. For example, in Figure 3, the Web author has created a section of information illustrating the specification of computer products and annotated the content based on the *SmartObject* class and its properties. In particular, the Web author has first annotated the whole information as a *SmartObject* and further annotated specific sections of the object according to the semantic meaning of the content, e.g., indicated that "Storage" is the title and "250GB HD" is the content of the *SmartObject*.

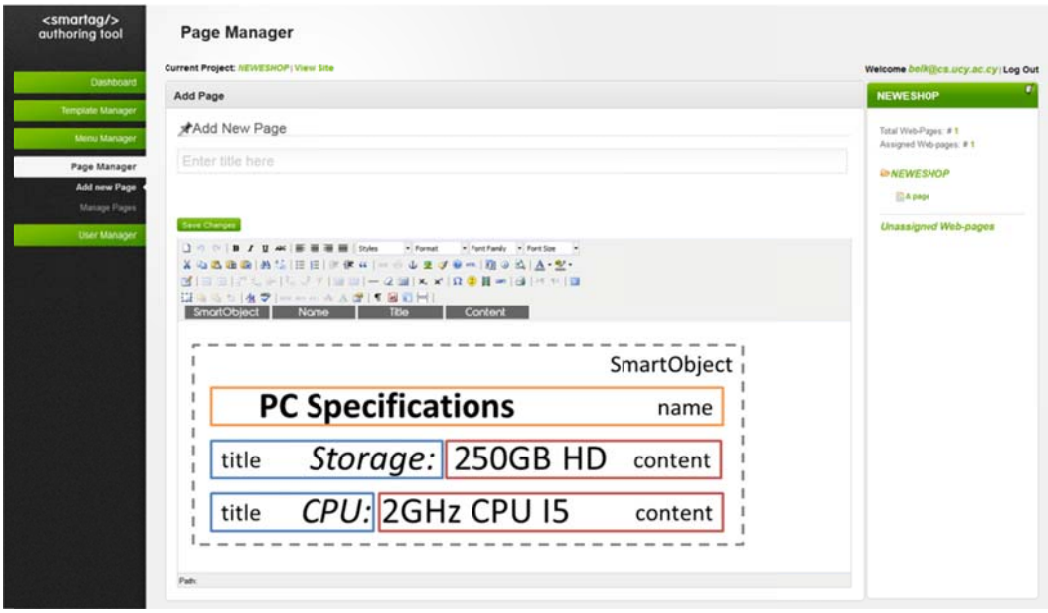

Figure 3. Semantic Authoring Tool

The annotated Web-page is then fed to the adaptation mechanism in order to adapt the content presentation of the RDFa-based *SmartObject* and users' navigation based on the proposed adaptation rules and effects described in the next sections.

3.3 Fuzzy Adaptation Mechanism

The adaptation mechanism is responsible for adapting the RDFa objects that are generated by the semantic authoring tool based on the cognitive characteristics of the user models, which are obtained from the user modeling mechanism. A Web browser extension has been developed in order for the Web browser to recognize and process the RDFa objects. A fuzzy rule-based mechanism was further utilized on the RDFa objects to provide the adaptation effects based on the users' cognitive characteristics.

Several options exist for developing a reasoning mechanism, e.g., probabilistic, Bayesian reasoning and fuzzy logic modeling. Accordingly, in this work the preferred method for adapting the environment of Web applications for individuals is Fuzzy Logic because human behaviour is usually characterized in fuzzy terms (i.e., Person A is more verbal than Person B and Person C is a lot more verbal than Person B would be used to describe the Verbal/Imager dimension of three individuals from the scale low, medium, high in the following order: B, A and C). Accordingly, a person is not necessarily part of a Verbal or an Imager class, but we feel that a person is better described as belonging to a Verbal class in a certain degree (i.e., 60%) and to an Imager class in another degree (e.g., 40%). To better explain this, we illustrate an example of how the decision or reasoning mechanism works on the one hand through crisp and on the other hand by fuzzy logic.

Suppose that an individual has a cognitive style ratio equal to 1.09. In crisp logic and for the Verbal/Imager dimension, this individual is considered to be an Imager. Figure 4 shows (a) how an individual is classified in a crisp class (left part) and (b) how an individual is characterized as low-Imager and belongs in a fuzzy class (right part).

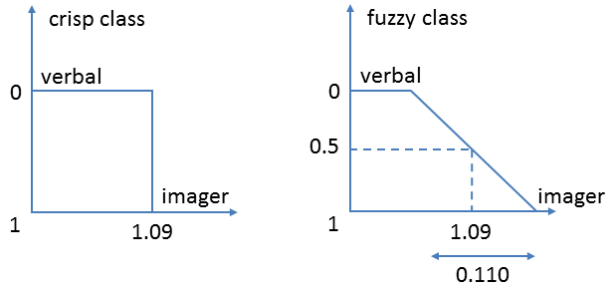

Figure 4. Example of a Crisp and a Fuzzy Class for the Verbal/Imager Dimension

Accordingly, in this work the predicted values of membership degrees to classes yielded from the ANNs are represented by memberships in fuzzy logic classes. A simple approach is followed for applying fuzzy logic principles; we consider only three or five values for the number of membership functions for each dimension (i.e., low, medium, high and very low, low, medium, high and very high). Then, this percentage of participation is used for adapting the environment of Web applications in small, medium, or high degree according to the membership value obtained. In the crisp case, the decision mechanism would include rules of the form: "*IF* an individual is Verbal *THEN* provide all content in a textual form" while in the fuzzy case the rule would be "*IF* an individual is low-Verbal AND high-Imager *THEN* provide all content through diagrams and images" which is definitely more informative and useful. In addition, the reasoning mechanism, provided by a group of experts, includes a set of rules taking into consideration: a) the Verbal/Imager dimension, b) the Analyst/Wholist dimension, and c) the Working Memory Span (WMS).

The fuzzy approach was applied in calculating the relative membership of each user in the three categories of cognitive typologies (i.e., Verbal, IntermediateV/I and Imager, and Wholist, IntermediateW/A and Analyst) and three categories of Working Memory Span (WMS) (i.e., Low, Medium and High). The approach introduces linguistic values stimulated by the membership functions as explained above and as shown in Table 2 and Figures 5-7.

Table 2. Values of the Bounds of the Membership Functions

	a1	**b1**	**c1**	**d1**	**a2**	**b2**	**c2**	**a3**	**b3**	**c3**	**d3**
Wholist/Analyst	-2.67	-2.27	1.02	1.15	1.02	1.18	1.35	1.25	1.35	2.01	2.01
Verbal/Imager	-2.67	-2.27	0.98	0.99	0.95	1.03	1.09	1.05	1.09	2.08	2.72
WMS	-2.67	-2.27	5	9	5	10.5	16	14	16.14	22	23

The process followed for fuzzification was based on triangular and trapezoidal membership functions, as described in equations (1) and (2) respectively:

$$\mu_t(x) = \begin{cases} \frac{x-a_t}{b_t-a_t}, & a_t \leq x \leq b_t \\ \frac{c_t-x}{c_t-b_t}, & b_t \leq x \leq c_t \\ 0, & otherwise \end{cases} \quad (1)$$

$$\mu_t(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a_t}{b_t-a_t}, & a_t \leq x \leq b_t \\ 1, & b_t \leq x \leq c_t \\ \frac{d_t-x}{d_t-c_t}, & c_t \leq x \leq d_t \\ 0, & d_t \leq x \end{cases} \quad (2)$$

In triangular memberships the function is estimated using three values, a, b and c which represent the left, centre and right points of the function.

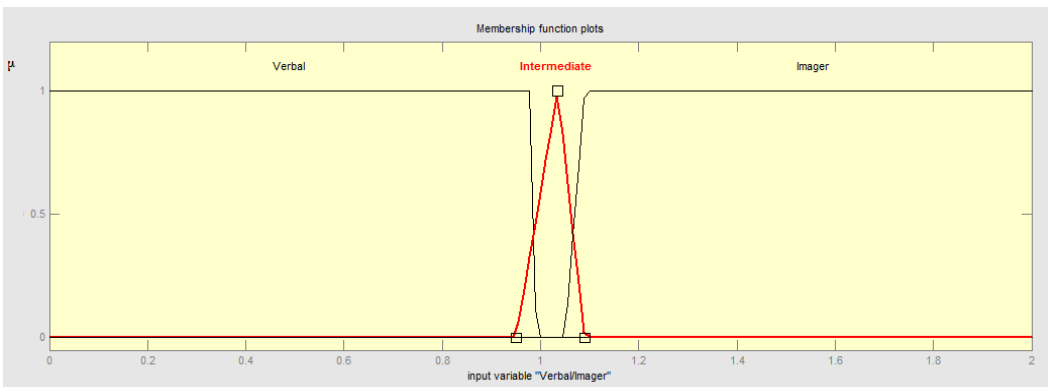

Figure 5. Trapezoidal and Triangular Membership Functions Used for the Verbal/Imager Types

In trapezoidal memberships the function is estimated using four values, a, b, c and d which represent the left, the left shoulder, the right shoulder and the right points of the function. The shape was chosen empirically by experts who also defined the bounds of the membership functions (Table 2).

The fuzzy expressions were implemented proportionally based on the original threshold of Riding's CSA. In this respect, given that the original Riding thresholds of the Verbal/Imager dimension were marginally close ($0.98 <= x < 1.09$), resulted in a marginal fuzzy expression. On the other hand, given that the original Riding thresholds of the Wholist/Analyst dimension, as well as the Working Memory dimension were

marginally larger (respectively, 1.02 <= x < 1.35, and 0 < x < 21) this resulted in a wider marginal difference in these two particular fuzzy expressions.

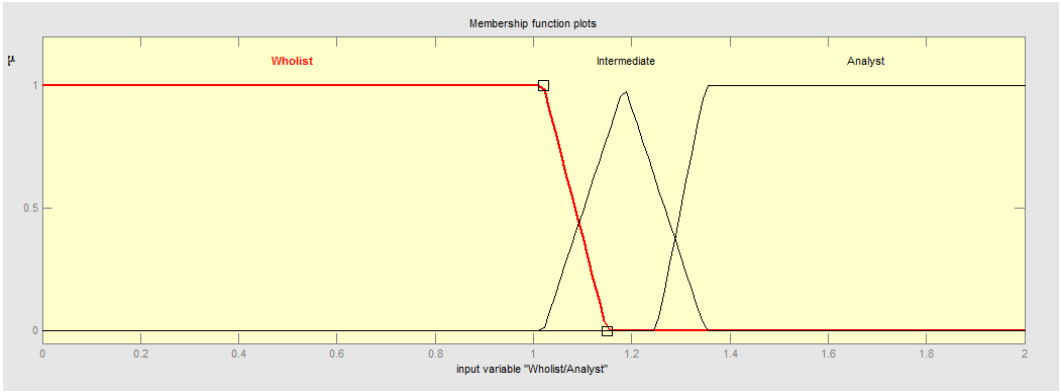

Figure 6. Trapezoidal and Triangular Membership Functions Used for the Wholist/Analyst Types

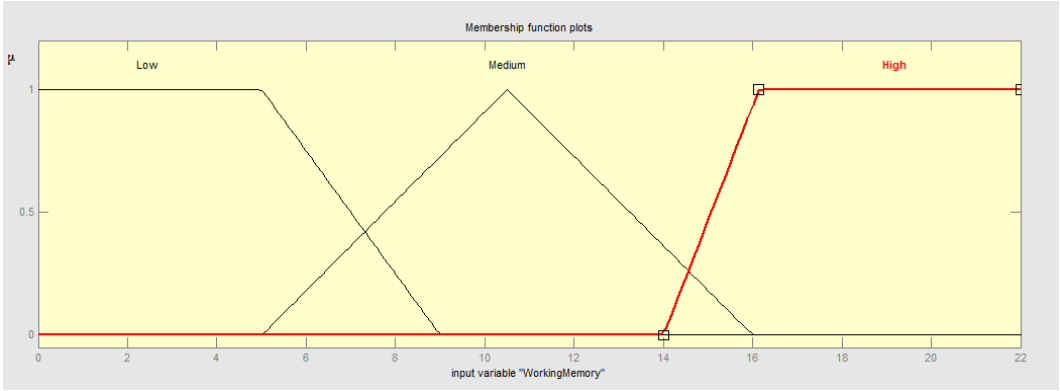

Figure 7. Trapezoidal and Triangular Membership Functions Used for the Working Memory Span

Finally, the process of defuzzification translates back the membership values of the corresponding fuzzy sets into a specific adaptation decision. In particular, based on the theory of individual styles described in the previous section, this work suggests the adaptation effects, illustrated in Table 3, which compose the reasoning mechanism using a set of fuzzy rules.

Accordingly, an example rule is: "*IF* a user is high-Imager AND has low WMS *THEN* provide an additional tool that allows the user to make entries of goal-related information in a diagrammatical representation". Accordingly, this approach enables users with low WMS to organize and access large amounts of information, alleviating disorientation and cognitive load caused by the high amount of information. The process

utilized the AND operator for calculating the minimum value of the partial membership functions of the user characteristics, while the maximum function was used for the corresponding OR parts of the rules for deciding on the adaptation effects. Another rule could be "*IF* a user is low-Imager AND has high WMS *THEN* provide to the user only specific sections of content in a diagrammatical representation that need a break down approach". For example the general description of a product is provided in textual form while the features and specifications of the product in a diagrammatical representation.

Table 3. Design Implications based on Cognitive Styles Theory

Imager	**Verbal**	**Analyst**	**Wholist**	**Intermediate**	**WMS (low)**
Presentation of information is visually enhanced in a diagrammatical form of representation	Usage of text, without visual enrichment	Content structure is chunked to clear-cut links to match analytical way of thinking	Content structure follows a more holistic pattern	Receive a condition balanced between the opposite preferences	Receive a tool for adding hyperlinks of the section the user visits

To this end, the mechanism explained was used for deciding on the adaptation effects of Web applications using notions of Fuzzy Logic. It reproduces human decision reasoning and includes concepts of partial truth. The main benefit is that it may continuously adapt the environment using new data as they become available and it is able to represent different levels of uncertainty while using the same decision model (rules and membership functions) and may thus cater for the particular needs of precision in different contexts and environments.

3.4 Adaptive User Interface

This section describes the adaptation effects based on the aforementioned adaptation mechanism. Figures 9 and 10 illustrate different example adaptation effects based on the original (non-adapted) version of the same Web environment (Figure 8).

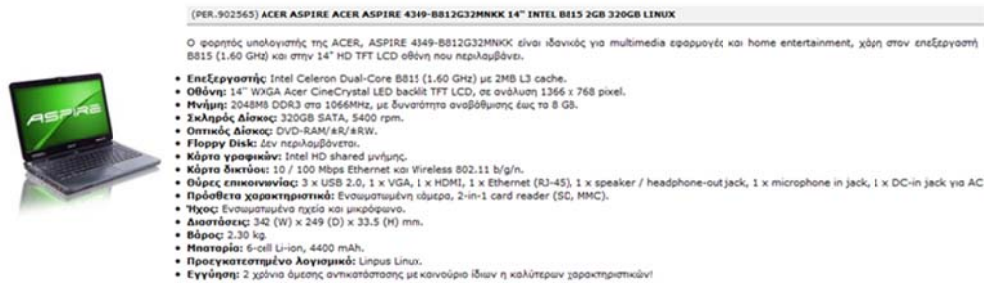

Figure 8. Original Web Environment

In the case of Figure 9, the user belongs to the Imager class and thus a diagrammatical representation of the containing information of the RDFa object is presented. The element property is used by the Web browser to distinguish the items (elements) of a *SmartObject* when creating a diagrammatical representation (e.g., Storage and CPU are two elements of the *SmartObject* instance reported in Table 1).

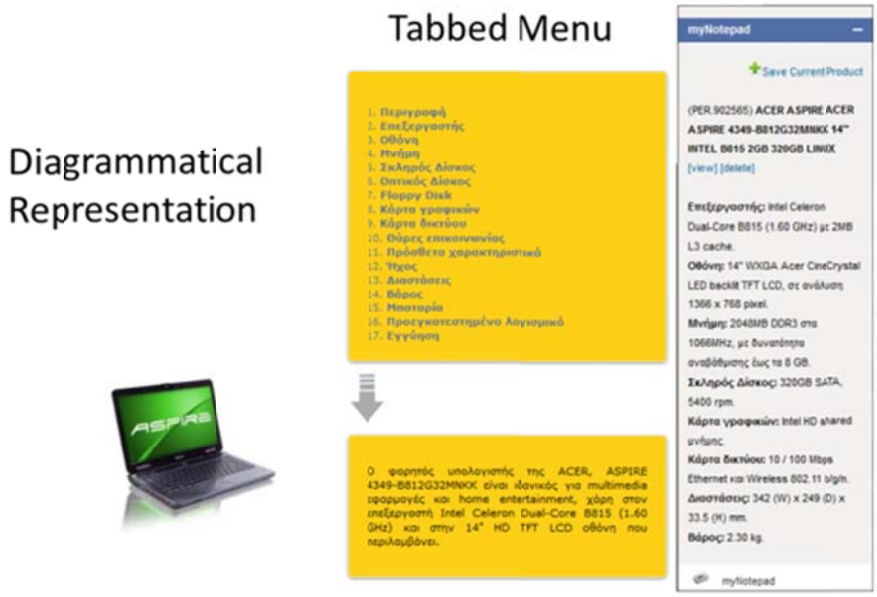

Figure 9. Adapted Web Environment (Imager/Analyst) with Content Support Tool (for users with Low WMS)

On the other hand, when a user belongs to the Verbal class (prefers verbal representations), as illustrated in Figure 10, no changes are made to the elements of the RDFa object. Furthermore, in case a user belongs to the Analyst class (Figure 9), the information will be enriched with a tabbed menu to arrange information in a manner that is closer to the analytic way of information organization. In particular, each item of the tabbed menu will consist of the title property of each RDFa element. This way, each item

of the menu is linked to the content property of a particular element. The same logic of transformation is used when mapping the RDFa object with a Wholist user (Figure 10). In this case, a dynamic floating menu with anchors is created so to guide the users on specific parts of the Web content while interacting. Again, the title property of the elements comprise the menu's items, linked to the content property of each element.

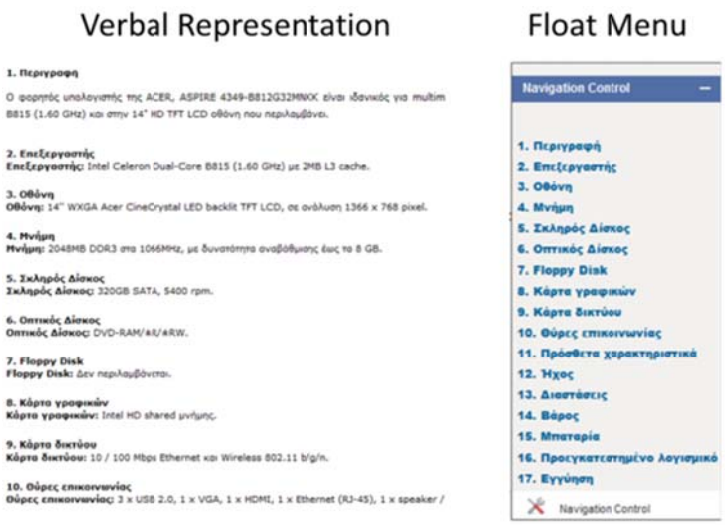

Figure 10. Adapted Web Environment (Verbal/Wholist)

Finally, in case users have low Working Memory Span (WMS) (Figure 9), the adaptation effect would be to provide them with a supportive tool for storing a section (element's title and content property) that the user is interested in until the completion of a cognitive task (i.e., "remember the specifications of a computer").

4. User Study

The aforementioned adaptation framework has been evaluated through a user study to investigate the effect of adaptation in Web applications based on cognitive factors.

4.1 Method of Study

A total of 50 undergraduate students participated voluntarily in the study (29 male, 21 female, and aged 17-25). All participants accessed a Web-site utilized for the

study with personal computers located at the laboratories of the University. The participants first provided their demographic characteristics (i.e., name, age, education, etc.) and performed a number of interactive tests using attention and cognitive processing psychometric tools [7, 38, 39, 40] in order to quantify their cognitive characteristics, as described in Section 3.2. Finally, the participants were asked to freely navigate in two different versions of a commercial Web-site selling computer products that was developed for the purpose of the experiment (i.e., original -non-adapted- and personalized -adapted- to their respective cognitive characteristics).

In particular, the participants navigated in two different versions of the same environment (i.e., original or personalized) and were asked to fulfill three tasks in each version. In particular, they had to find the necessary information to answer three sequential multiple choice questions that were given to them while navigating. All six questions were about determining which laptop excelled with respect to the prerequisites that were set by each question. The selection process of the sequence of version per individual was based on a random selection process. As soon as users finished answering all questions in both versions, they were presented with a satisfaction questionnaire. The questionnaire was based on the WAMMI (Website Analysis and MeasureMent Inventory) [49] where users were asked to choose which environment was better (using a scale from 1-5, where 1 means strong preference for environment A - original - and 5 for environment B - personalized), with respect to usability factors.

The dependent variables of the study utilized as indicators of differences between the two versions were: i) Task performance (efficiency), ii) Task accuracy (effectiveness), and iii) User satisfaction.

4.2 Analysis of Results

For our analysis, we used ANNs to estimate the fuzzy membership values in each fuzzy set based on the ratios of Riding's CSA test and thus each user belonged at the same time in each class to a certain degree. The respective degree was taken into consideration when the adaptation was decided. Following, we analyze the task performance, accuracy and satisfaction based on the personalized and original environments. The sample consisted of the following users (based on Riding's CSA):

Wholists (N=17, f=34%), IntermediatesW/A (N=10, f=20%), and Analysts (N=23, f=46%), ii) Verbals (N=20, f=40%), IntermediatesV/I (N=18, f=36%), and Imagers (N=12, f=24%), and iii) Low Working Memory Span (N=12, f=24%), Medium (N=31, f=62%), and High (N=7, f=14%), which consisted of participants that have had limited, medium and enhanced working memory capacity, respectively.

Task Performance. Results revealed that users performed faster in the personalized environment with a mean of 56.03 secs for completing all three tasks compared to 65.38 secs for completing all three tasks in the original environment. A three by two way factorial analysis of variance (ANOVA) was conducted aiming to examine main effects between the users' cognitive factors (i.e., Wholist/Analyst, Verbal/Imager, and Working Memory dimensions) and environment type (i.e., personalized vs. original) on the time needed to accomplish the given task. Figure 11 illustrates the means of performance per cognitive factor group in both Web environments and Tables 4-6 summarize the performances of each cognitive factor group per task. In regards to the Wholist/Analyst dimension, the analysis revealed that users belonging to the Wholist and IntermediateW/A classes performed considerably faster in the personalized version of the environment than in the original version (Wholist: $F(1,33)=1.721$, $p=0.199$, IntermediateW/A: $F(1,19)=3.402$, $p=0.082$). In contrast, users belonging to the Analyst class did not perform significantly different in either of the two environments ($F(1,45)=0.023$, $p=0.879$). Results indicate that the adaptation effects provided to Wholist and IntermediateW/A users improved their task completion time and thus worth further investigation for improving user interactions in such environments.

Table 4. User Performances (in secs) for completing the Tasks for the Wholist/Analyst Dimension

	Task 1		**Task 2**		**Task 3**	
Cognitive Styles	Original	Personalized	Original	Personalized	Original	Personalized
Wholist	86.67	**78.74**	89.4	**59.45**	43.57	**37.28**
IntermediateW/A	**69.8**	72.06	61.88	**45.61**	50.54	**29.77**
Analyst	**102.88**	122.82	60.94	**59.09**	44.31	**38.39**

On the other hand, the adaptation effects provided to Analysts did not help improve the users' performance. In this respect, other adaptation types (instead using a tabbed menu) should be investigated to examine whether interactions of this user class could be improved in terms of task completion time.

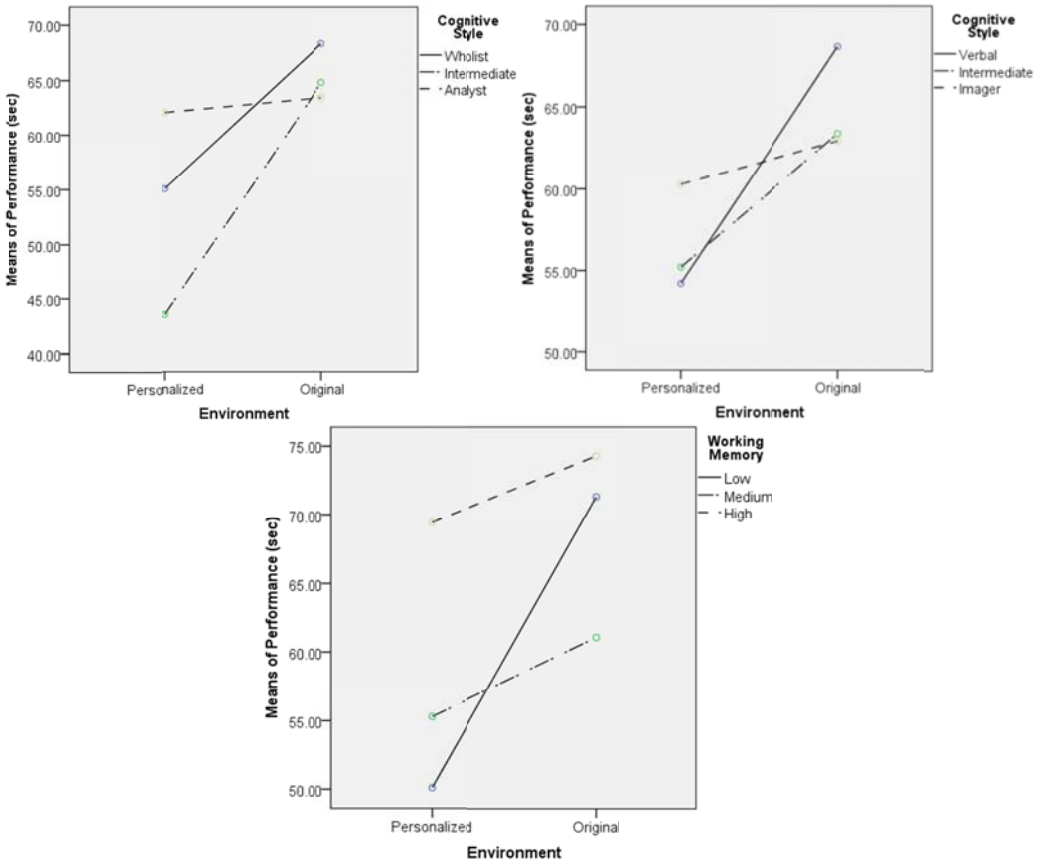

Figure 11. Means of Performance per Cognitive Factor Group

Furthermore, based on Table 4, users across all three groups performed faster in the personalized version for Tasks 2 and 3 while for Task 1 a mixed performance between the groups has been observed. This might be due to the fact that the first task required by the users to first get familiar with the environment before completing the task. Nevertheless, the results again reveal that Wholists primarily benefited more by the personalized version rather than the original one, as they performed all three tasks faster in the personalized version. Accordingly, given that Analyst users follow a scattered approach in navigation, are considered more independent, without needing much guidance, and also operate by breaking down information in an analytic manner [38],

results have shown that by providing them specific adaptation effects (in our case a tabbed menu for activating/deactivating specific sections) might not necessarily affect their performance. On the other hand, given that Wholists tend to rely on information provided by the outer world and needing more guidance than Analysts [38], the results have shown that the added navigational tools provided for guidance have affected positively their performance in the personalized version.

With regard to the Verbal/Imager dimension, the analysis revealed that users of all three classes (Verbal, IntermediateV/I, Imager) performed considerably faster in the personalized version of the environment than in the original version ($F(2,99)=0.314$, $p=0.731$) with Verbals and IntermediatesV/I being notably faster in the personalized version. Although the results regarding this cognitive style dimension were not statistically significant, they suggest further investigation since all users completed their tasks faster in the personalized than in the original version indicating that adapting content presentation based on cognitive styles improves task completion efficiency. In particular, the diagrammatical representation of content seems to help Imagers process information more efficiently than the plain text-based content as was in the case of Verbals.

Table 5. User Performances for each Task for the Verbal/Imager Dimension

	Task 1		**Task 2**		**Task 3**	
Cognitive Styles	Original	Personalized	Original	Personalized	Original	Personalized
Verbal	97.24	**93.72**	67.76	**53.11**	43.44	**35.14**
Intermediate V/I	**74.75**	99.59	75.89	**58.00**	52.07	**37.71**
Imager	103.95	**101.41**	68.25	**59.97**	38.26	**36.29**

Similar to Table 4, users across all three groups performed faster Tasks 2 and 3 in the personalized version rather than the original environment. In the case of Task 1 that required some time for the users to familiarize with the environment, IntermediatesV/I performed faster in the original version, while Verbal and Imager users performed Task 1 faster in the personalized environment rather than in the original environment.

Finally, regarding the working memory dimension results have shown that users with limited working memory capacity performed faster in the personalized version

suggesting that the tool for storing the summary of each product improved their task completion performance (F(1,23)=3.478, p=0.076). Users with medium and enhanced working memory capacity did not perform significantly different in either of the two environments since these two user classes did not receive any tool for comparing different products as was in the case of users with limited working memory capacity.

Table 6. User Performances for each Task for the Working Memory Dimension

	Task 1		**Task 2**		**Task 3**	
Working Memory	Original	Personalized	Original	Personalized	Original	Personalized
Low	93.08	**82.78**	79.14	**49.65**	45.35	**30.09**
Medium	**87.39**	98.44	62.7	**56.75**	42.51	**37.12**
High	**101.66**	119.86	92.42	**67.23**	57.58	**43.25**

Based on Table 6, medium and high working memory users were faster in completing Task 1 in the original version of the environment, whereas they performed faster the rest tasks (Tasks 2 and 3) in the personalized version. In the case of low working memory users, the temporary storage tool for keeping active specific sections of the content seems to have benefited their performance as they completed all three tasks faster in the personalized version than in the original version.

Task Accuracy. In order to assess the significance and possible impact cognitive factors may have on the adaptation of content and functionality of Web applications in terms of task efficiency, a comparison has been performed between the average correct answers the users provided in each version (i.e., original and personalized), as illustrated in Figure 12. Users in the personalized version were consistently more accurate in providing the correct answer for each task. In particular, users in the original version had a mean of 56.03% correct answers, while in the personalized version the same mean rose to 65.38%. A further analysis was conducted that aimed to compare the average correct answers per user group in each version. In regard with the Wholist/Analyst dimension, IntermediateW/A users were considerably more accurate in completing the tasks (personalized version: 80% correct answers, original version: 63.33% correct answers), whereas in the other two user classes, the task accuracy was not significantly different.

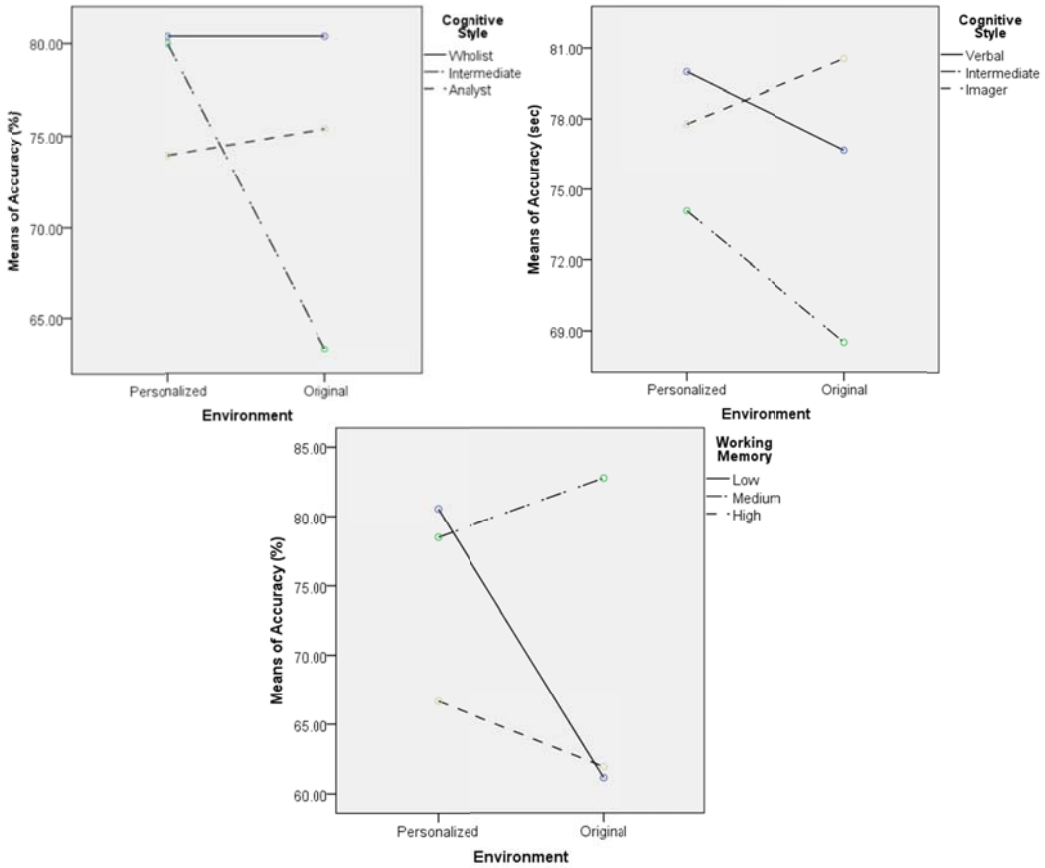

Figure 12. Means of Task Accuracy Scores per Cognitive Factor Group

In the case of the Verbal/Imager dimension, Verbals and IntermediatesV/I were considerably more accurate in the personalized version than in the original version, whereas Imagers the opposite. The main interpretation of this result is that this particular dimension (Imager) primarily affects the user preference of content representation (i.e., diagrammatical representation), rather than task completion performance [36, 38]. Nevertheless, further studies with a larger sample need to be conducted to reach to more concrete conclusions about the particular adaptation effect of Imagers on their task performance. Finally, users with limited working memory were remarkably more accurate in the personalized version with 80.55% correct answers, compared to 61.11% correct answers. Users with medium working memory capacity were slightly more accurate, whereas users with enhanced working memory capacity the opposite. A possible interpretation of this result is that users with medium and enhanced working memory capacity did not receive any additional tool for keeping active specific sections of the content, as was in the case of limited working memory users, and thus no

considerable differences were observed between the two environments in terms of task accuracy.

To this end, although the difference of accuracy between the two versions was not significant in many cases, results are encouraging for the proposed mechanism, implying that adaptation on the basis of these cognitive factors (cognitive style and WMS) provides adaptation effects that benefits users within an eCommerce environment. A further analysis with a greater or more diverse sample is required in order to draw even more concrete conclusions.

User Satisfaction. A questionnaire was utilized to retrieve the users' perceptions regarding the two environments (i.e., original vs. personalized). In particular, users were asked in which environment they could find easier and faster the information they were looking for. The constructs of the questionnaire are: Attractiveness, degree to which users like the Web-site; Control, degree to which users feel "in charge" of the Web-site; Efficiency, degree to which users feel that the Web-site provides the information they are looking for within a reasonable timeframe; Helpfulness, degree to which users feel that the Web-site enables them to solve their problems with helpful tools or by finding helpful information; Learnability, degree to which users feel they can get to use the Web-site if they access it for the first time. Results of the questionnaire are depicted in Figure 13.

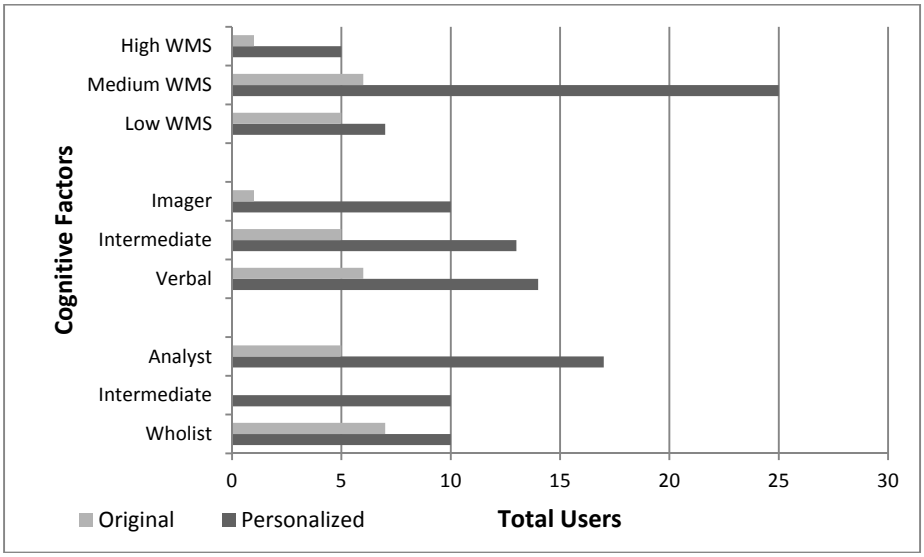

Figure 13. Users' Questionnaire Answers per Web Environment

Results revealed that 38 users (76%) preferred the personalized environment and 12 users (24%) preferred the original environment, while 1 user had neutral preference. A binomial statistical test was conducted (H0: p(original)=0.5 and p(personalized)=0.5) indicating that there is significant preference of users toward the personalized environment ($p<0.01$).

Furthermore, a chi-square test was conducted to examine whether there is a relationship between users' cognitive characteristics (i.e., cognitive styles and Working Memory Span (WMS)) and the usability factors of each environment (i.e., original or personalized). The analysis revealed that 83% of the Imagers, found the personalized version significantly more attractive ($p=0.039$). Such finding suggests that presenting content in an adaptive format (e.g., diagrammatical representation to Imager users) improves the attractiveness of the Web environment. Another interesting finding was the fact that 78% Analysts could complete their tasks more efficiently and had more control of the environment ($p=0.011$). Such finding indicates that the navigation control tools (i.e., tabbed menu) provided to the users in the personalized version improved the usability of the system in terms of user control and task efficiency.

Finally, examining the relationship between the WMS and preference toward a specific environment has revealed that 67% users with limited working memory capacity found the personalized environment more efficient and controllable ($p=0.338$). Although the analysis did not reveal significant relationship between the two factors, such finding is encouraging for further research since the analysis revealed that providing a supportive tool for keeping active information during a task is helpful for the users.

Rule-based vs. Fuzzy-based Mechanism. The research reported in this paper is an extension of prior work of the authors [3] which has revealed a main effect of cognitive factors on the adaptation and personalization process of interactive systems. Given that the previous work utilized a deterministic rule-based mechanism for providing different predefined Web environments to users based on their cognitive style, main aim of this section is to compare the effects of personalization according to the adaptation process followed in each case, that is, compare the rule-based approach and predefined environments, with the new enhanced fuzzy-based approach and dynamically created

environments based on semantically enriched content. Table 7 summarizes the overall task performance, accuracy and user satisfaction of the adapted and non-adapted versions in each approach.

Table 7. Comparison of Results of the Rule-based [3] and Fuzzy-based Approach

	Performance		**Accuracy**		**Satisfaction**	
Approach	Original	Personalized	Original	Personalized	Original	Personalized
Rule-based	180 sec	**137 sec**	30%	**60%**	25%	**43%**
Fuzzy-based	65.38 sec	**56.03 sec**	56%	**65%**	24%	**76%**

The results obtained from both approaches reveal improvements in task completion time and task accuracy as well as user satisfaction. In particular, performance and accuracy is significantly improved in the rule-based approach, whereas the fuzzy-based adaptation mechanism considerably improves the satisfaction levels compared to the original environment.

5. Conclusions

The basic objective of this paper was to propose a framework for Web adaptation using cognitive factors. In particular, Computational Intelligence techniques which utilize Artificial Neural Networks and Fuzzy Logic for developing and adapting Web applications based on a combination of human factors, namely cognitive styles and working memory were used. A user study utilizing the proposed technique was conducted to investigate the effect of fuzzy adaptation in Web applications based on the cognitive characteristics of users.

It was demonstrated that users' information finding ability was considerably more accurate and efficient in the personalized version rather than the original version of the same application. The observation was made in terms of both providing correct answers to the questions asked (task accuracy) and in task completion time (performance). In particular, the personalization provided seems to have benefited primarily the Wholist and IntermediatesW/A, and users with low working memory capacity. This might be explained by the fact that Wholists tend to rely on information provided by the outer world and need more guidance [38] in comparison to Analysts, and thus the added navigational tools provided for guidance have affected positively their performance in the

personalized version. On the other hand, performances of Analysts in both versions did not have considerable differences indicating that the additional navigation tool provided has not significantly affected their performance. Furthermore, users with low working memory performed faster in the personalized version. Such a result increases the external validity of the work since the work in [3, 50] has revealed that users with low working memory are positively affected by adaptation and personalization effects. Additionally, users preferred the personalized version of the environment and results revealed that the majority of users could find the information they were seeking much easier and faster. Another important finding was the fact that presenting the content in a diagrammatical representation (for Imagers) has significant main effect on the attractiveness of the Web environment. Furthermore, the analysis revealed that there is a noticeable relationship between the Wholist/Analyst dimension, and the control and efficiency factors of the Web environment, indicating that the adaptive navigation control tools improved the usability of the Web environment. These findings are in-line with previous research [51] and are encouraging and pave the path for further research and analysis since in general, users' preference leans toward the personalized version indicating that the proposed mechanism has provided appropriate adaptation effects in relation to the cognitive characteristics of users.

Future research prospects include conducting further studies with a bigger and a diverse sample in order to establish a more rigid connection between human factors and information processing in Web applications. A further evaluation of the proposed fuzzy approach in adaptation is planned with the aim to compare the effects of adaptation between rule-based and fuzzy-based techniques. Finally, further user studies with non-computer-expert users are considered to analyze user performance and obtaining larger variability of the results.

Acknowledgements. The work is co-funded by the PersonaWeb project under the Cyprus Research Promotion Foundation (ΤΠΕ/ΠΛΗΡΟ/0311(ΒΙΕ)/10), and the EU projects Co-LIVING (60-61700-98-009) and SocialRobot (285870).

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