Enhancing the Learning Experience: Preliminary Framework for User Individual Differences

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Abstract. A system able to adapt to different user characteristics may increase user's learning outcome and advance her/his personal learning experience. This paper reports on research identifying and appraising user personal differences employed in user modelling for adaptive educational systems. A preliminary set of individual characteristics relevant for adaptation is proposed, along with a framework for their categorization. The framework is derived on the basis of empirical studies and survey papers reviewing the usage of these variables in adaptive and adaptable systems. Each variable is addressed from the perspective of its definition, implementation in existing systems and relevance for adaptation. Methods for variable detection and quantification are discussed as well. Suggested framework represents authors' perspective of the state-of-the-art in analyzing user individual differences and adds to the body of knowledge related to the user analysis as an essential part of an adaptive system development process.

Keywords: User experience; user individual differences, user modelling, web-based learning.

1 Introduction

Current research acknowledges that understanding users and diversity in their backgrounds, skills, goals and needs is at the core of successful design of information society technologies (IST) products and services. Furthermore, the need for accessible and usable learning in knowledge society for all promotes e-learning that engages users effectively. From this perspective, the role of transparent system interface and intuitive interaction tailored to unique personal requirements is crucial. Regarding the design of effective e-learning systems, the interface adjusted to individual differences of each particular user/learner should be able to advance users' personal learning experience and consequently increase their learning achievements. In such a context, it is crucial to conduct research that embraces and relies on innovations in user sensitive design. The influence of user goals, knowledge, preferences, styles and experience on her/his interaction with a system is unquestionable and studies have already empirically proved that system intelligent behaviour relies on individual differences e.g. [4, 6, 14, 36]. However, adaptive systems development is the process that includes comprehensive research, in relation to the application domain of a particular

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system. Designing intelligent interaction needs to take into account several research questions: how to identify user characteristics relevant for the application domain, how to model the user, what parts of the adaptive system shall change and in what way and finally how to employ user model to implement adaptivity, cf. [4, 40]. Research presented in the following addresses the first issue in the context of the web-based learning design.

The goal of this paper is to summarize and report on a survey on user individual differences that aid in the development of successful e-learning applications able to increase users' learning outcomes and advance their personal learning experience. Based on empirical studies and surveys on existing adaptive systems we have constructed a preliminary framework for categorization of user individual characteristics employed as sources for adaptation in adaptive educational systems (AESs).

Each adaptive application has certain specific features and specific target user groups, so there is no unique "set" of user model variables appropriate for all AES's. Having that in mind, the recommended framework could be considered as an authors' perspective of the state-of-the-art in analyzing user individual characteristics and intends to serve as a basis for user analysis as a starting point of any adaptive system design. User analysis in a learning context encompasses identification and acquisition of relevant user's information. Specifically, it enables the recognition of the individual user features that are the most important for the enhancement of user experience, the increase of learning achievements (as an objective measurable effect), along with the improvement of satisfaction in system usage.

The paper is structured as follows. Section 2 offers a brief review of studies of individual differences from a historical perspective. Section 3 describes related work and presents a framework for user individual characteristics as sources for adaptation. Section 4 summarizes and discusses the suggested framework, while the final section concludes the paper.

2 Brief Historical Background on User Individual Differences

The initial comprehensive overview of individual differences in the HCI field is Egan's [15] report on diversities between users in completing common computing tasks such as programming, text editing and information search. He pointed out that the ambition of adaptivity is that not only "everyone should be computer literate" but also that "computers should be user literate", suggesting that user differences could be understood and predicted as well as being modified through the system design. Since then, the diffusion of technology brought computers to the wide user population with extensive variety of knowledge, experience and skill dimensions in different areas. Accordingly, identification of individual differences relevant for a system adaptation became a critical issue. In their early consideration of adaptivity, Browne, Norman and Riches [3] provided one of the first classifications of candidate dimensions of user differences that may impact computer usage. They included diversities in cognitive styles (field dependence/independence, impulsivity/reflectivity, operation learning/comprehension learning), personality factors, psycho-motor skills, experience, goals and requirements, expectations, preferences, cognitive strategies and a number of cognitive abilities. Later on, Dillon and Watson [14] reviewed a century of individual differences work in psychology stressing the role of differential psychology in the HCI field. They have identified a number of basic cognitive abilities that have reliably influenced the performance of specific tasks in predictable ways. Based on their own analyses, they concluded that measures of ability can account for approximately 25% of variance in performance, thus being suitable for usage in decision making for most systems, especially in addition to other sources of information (previous work experience, education, domain knowledge, etc.). According to their recommendations, psychological measures of individual differences should be used to increase possibilities for a generalization of HCI findings. There is a number of studies confirming these pioneer work suggestions, showing for example that cognitive abilities, such as spatial and verbal ability, do affect the interaction, particularly the navigation performance of the user [2, 10, 33, 49, 61].

The influence of user goals, knowledge, preferences and experience on her/his interaction with an intelligent system is unquestionable [4]. Moreover, these characteristics have been successfully employed in many adaptive systems, for example AHA! [12], InterBook [5], KBS Hyperbook [29], INSPIRE [41], AVANTI [51], PALIO [52].

On the other hand, the matter of adaptation to cognitive styles and learning styles has been mainly ignored or marginally addressed until a last decade. Nevertheless, latest research confirms that navigation preferences of users reflect their cognitive styles in several dimensions: field dependent vs. independent, as defined by Witkin, Moore, Gooddenough and Cox [60], holist vs. serialist [42], verbalizer vs. imaginer [46]. In a related study, Chen and Macredie [9] found that field dependent learners prefer guided navigation, while field independent favour navigation freedom. Graff [26] also showed that individuals identified as having verbaliser and imager cognitive styles apply different browsing strategies.

In the educational area, many authors have concluded that adaptation to learning styles, as defined, for example, by Kolb [35] or Honey and Mumford [30], could bring potential benefits to students' learning activities. This is evident from an increasing number of AES's having implemented some kind of adaptation (adaptability or adaptivity) to learning styles, see for example CS388 [8] or INSPIRE [41].

Evidently, the effect of user individual differences on her/his performance has been the topic of a very fruitful research for the last few decades. However, the obtained results are not quite consistent, partially because the user performance while using a particular system depends greatly on the system itself [3]. In addition, the research on cognitive styles and learning styles in the HCI field is emerging. There is yet no strong evidence of their relevance concerning user's interaction with an intelligent system, as also discussed in [50]. Furthermore, even if these user styles were proved to be relevant, the question of potential benefits from personalized interaction still remains. System adaptation, even when well designed, does not necessarily imply user's performance improvement *cf.* [9]. Moreover, it can be disadvantageous to some classes of users [11]. From this rationale, it is worthwhile to consider possible alternatives before deciding to include adaptation into a system. An enlargement of learner's experience to overcome her/his low spatial ability [1] or an appropriate redesign of a non-adaptive interface [31] could be considered as alternatives.

Based on these reflections, we have conducted an empirical user analysis regarding a web-based learning application [38]. User individual characteristics concerned as predictor variables included age, personality factors, cognitive abilities, experience, background knowledge, motivation and expectations from e-learning. The study revealed that the students' intelligence, in terms of the Spearmans' "g" factor [53], hyperspace experience and motivation has a statistically significant correlation with learning outcomes acquired in e-learning environment. Obtained results are in line with general expectations, but now have been empirically proven, adding to the body of knowledge on user individual differences.

3 Preliminary Framework for User Individual Differences

There is a large amount of related work summarizing the influence of user individual differences on user's interaction with an adaptive system. A majority of such papers have listed adaptive systems with their user model variables, detection mechanisms and adaptation techniques applied, e.g. [47]. However, there is a significantly lower number of papers attempting to summarize all the variables employed as user model attributes in existing systems. One can easily find reviews of adaptive systems accommodating one user individual characteristic, for example cognitive styles [9] or learning styles [41, 23], but there is a lack of papers offering a systematization of variables used as sources for adaptation in existing adaptive systems.

Focusing on variables instead on systems, Triantafillou and Georgiadou [55] examined variables that can initiate adaptation and discussed their potential use in a hypothetical student model for computerized adaptive testing. Their list of "adaptive variables" emerged from five survey articles. On the contrary, Thalmann [54] concluded his own list of "adaptation criteria" based on structured content analysis of 30 existing adaptive hypermedia systems. His review provided suggestions for the preparation of a learning material with respect to the identified adaptation criteria, even though it did not consider any cognitive abilities or cognitive styles. Grimley and Riding [28] concluded that cognitive style, gender, working memory, prior knowledge and anxiety have significant impact on web-based learning. They have described those concepts, placed them within the context of learning and proposed the ways of adapting the learning environment to each individual user. Still more applicable suggestions for user model construction and maintenance could be found in [7]. This review represents user models of adaptive web-based systems from three aspects: what is being modelled, how it is modelled, and how the models are maintained.

Regarding user models of existing adaptive systems, in this paper a preliminary framework is established for user individual characteristics that are, or could be employed as sources for adaptation in e-learning systems. The classification is derived from the review of empirical studies and survey papers on existing AES's, acknowledging the relevance of those variables for system adaptation. Identified characteristics are classified in three broad categories:

ii) *personal user characteristics*: age, gender, cognitive abilities, personality, cognitive style and learning style;

iii) *previously acquired knowledge and skills*: experience, psycho-motor skills and background knowledge;

iiii) *system related user characteristics*: goals, requirements, preferences, interaction styles, motivation and expectations.

Following subsections describe each one of the identified characteristics in detail. For each recognized variable three significant aspects are addressed – its definition, implementation in existing systems and evaluation of its relevance for adaptation. Additionally, methods used for detection and quantification of described characteristics are also reported. The framework is briefly summarized in Table 1, subsequent to the descriptions of the identified variables.

3.1 Personal User Characteristics

This category comprises general user information, such as age and gender, along with user individual traits. Concerning diversities in *age*, the more heterogeneous the user population is, the influence of age on user performance is greater. Age, experience and background knowledge are certainly not independent variables. Their influence on success of user interaction is naturally overlapping to some extent. Still, age is often a good predictor of user performance for individuals who are novices in using complex systems [15]. In addition to that, Ford and Chen [20] found differences in navigation behaviour of students using a hypermedia learning system, related to their age. In the same study they have obtained a statistically significant correlation of *gender* with the number of requests for guidance. Female students asked for less guidance, they have displayed a relatively extrinsic motivation for attending the learning session and have successfully completed a greater number of tasks compared to males. *Individual traits* are user features that define a user as an individual: cognitive abilities, personality, cognitive styles and learning styles. These features are very steady over time and they are usually assessed by reliable psychometric tests, under the supervision of a psychologist conducting the tests and interpreting the results. The research on individual traits and their use for adaptation is emerging, especially on the use of cognitive and learning styles. Progress is also evident in examining new methods for detection and quantification of individual traits during the interaction.

Cognitive abilities. Among many classifications of cognitive abilities [14], there are several characteristics which seem to be relevant for HCI: general intelligence, spatial, verbal and visual ability, reasoning aptitudes, perceptual speed, working memory capacity and others. The impact of these characteristics on users' interaction was confirmed in numerous studies, both early and recent [2, 15, 25, 39].

Spatial ability is the ability to perceive spatial patterns, or to maintain orientation with respect to objects in space [16]. HCI research often uses this term to annotate the ability of mental manipulation of 2-dimensional and 3-dimensional figures, and sometimes to annotate the ability of memorizing spatial arrangement of objects, e.g. [3]. However, among all cognitive abilities, spatial ability is the most cited as a good predictor of user performance, especially considering navigation [2, 10, 33, 49, 61]. Spatial ability is traditionally assessed by psychometric tests; yet another approach to dynamic detection of spatial aptitudes could be found in AKBB [27].

Compared to spatial ability, a significantly smaller part of literature deals with other cognitive abilities. Norcio and Stanley [39] reported few studies that have found the influence of *reasoning aptitudes* and *verbal ability* on computer usage. Dillon and

Watson [14] quoted several studies that examined the influence of user's *perceptual speed*, logical reasoning and *visual ability*. They reported differences in user performance related to logical reasoning and visual ability and confirmed that these user differences could be reduced by appropriate training and/or interface design. More recent work acknowledges the effect of *working memory capacity* on educational achievement in terms of problem solving, reasoning and reading comprehension [28], but possibilities for adaptation of e-learning systems to models of learning concerning working memory are still in an exploratory phase.

Personality. According to Eysenck [17] two main personality factors are *extraversion vs. introversion* and *neuroticism vs. emotional stability*. The extraverts tend to be more physically and verbally active whereas the introverts are independent, reserved and steady. The person in the middle of the dimension likes a mix between social situations and solitude. Neuroticism is the tendency to experience negative emotions or nervousness. On the other hand, emotional stability is related to calm, stable and relaxed persons. Personality concerns characteristics which remain stable over time and across situations, often considered as part of user individual traits that generally reflects on the way she/he uses a computer system [3, 4, 47]. In particular, Richter and Salvendy [45] compared the performance of extraverts and introverts using system interfaces with personality attributes added. Their results showed that the interface designed with introverts' personality attributes generally results in the fastest performance for both extraverts and introverts.

Cognitive styles. This is a relatively stable category of user individual differences related to information processing patterns in general context. Among various dimensions of cognitive styles, *field dependence/independence* (FD/FI) is probably the most exploited in adaptive systems, especially in the educational domain. According to Witkin, Moore, Gooddenough and Cox [60], FI individuals follow an analytical approach and study one topic in detail before reading the other. Conversely, FD users see the global picture first and concentrate on the details afterwards. FI users tend to develop self-defined goals and reinforcements, while FD individuals require externally defined goals and reinforcements.

In related research, Pask [42] studied global/analytic differences concerning learning of complex academic subject matters and identified *holist vs. serialist* approach to learning. Holist individuals process information in relatively global ways, similar to FD users, whereas serialist individuals use relatively analytic approach, similar to FI users. Moreover, Ford and Chen [20] found statistically significant correlations between these cognitive style dimensions. According to the scores of psychological tests, Pask's holistic cognitive style is connected with FD style, while serialist cognitive style is connected with FI style. This result suggests that the holist and FD learner use similar learning strategies, as do the serialist and FI learner.

User differences in cognitive styles result in different learning strategies in virtual learning environments. Chen and Macredie [9] found that FD learners use guidance through instructional content, while FI learners prefer to create their own path of learning topics. In the same study, they have empirically confirmed that FI learners explore each topic in depth before reading another topic. On the other hand, FD learners first run through the whole content of the course and then concentrate on a single topic. User differences in cognitive styles have been successfully applied in implementation of different strategies for instructional design in several AESs, e.g. [20, 50]. On the basis of different learning behaviour displayed by FI and FD learners [9], De Bra, Smits and Stash [13] speculate that at least field dependent learners should benefit from providing an introductory page on each major topic that would be offered before presenting the whole material on the topic. They also recommend two different ways of designing such introductory pages.

Another commonly exploited dimension of cognitive styles is *verbaliser/imager* [46]. Verbalisers usually prefer textual modes of presentation while imagers prefer non-textual modes (for example pictorial and diagrammatic information), especially while illustrating, or elaborating on initial textual information. This dimension of cognitive styles has been shown to affect browsing strategies [26] and learning preferences [48]. It is implemented, e.g. in AHA! [50] using the conditional inclusion of objects, but without enforcing the use of certain media types.

Graff [26] showed that imagers tend to see their environment as a whole in a complex hypermedia architecture. However, measurement of the depth of browsing did not show differences between verbalisers and imagers. Comparing this result with findings of Ford and Chen [20], it appears that imagers do not display exactly the same strategies as holists and field dependent learners in their tendency to see the overall structure of the learning content. This is just another empirical confirmation for the rationale that various dimensions of learner cognitive styles produce different learning strategies and that they should be considered as different variables in development of AES's.

Learning styles. In HCI literature, newer research emerged on a variety of learning style models and categorizations, e.g. [23, 40]. Here, we consider learning styles strictly as user preferred strategies of learning, contrary to some authors who consider cognitive styles displayed in the learning process as learning styles.

On the basis of Kolb's theory of experiential learning [35], Honey and Mumford [30] classify learners into four types: *activists, pragmatists, reflectors* and *theorists*. This learning style model is commonly implemented in existing AES's, for example INSPIRE [41]. Implementations of Felder–Silverman learning style model [18] can also be frequently found in adaptive systems, e.g. CS388 [8] and SAVER [22]. This model characterizes each learner according to four dimensions: *active/reflective, sensing/intuitive, visual/verbal* and *sequential/global* learner.

A number of researchers have reported improved learning performance of students whose learning styles matched the presentation mode. Ford and Chen [21] have found a significant difference in performance on conceptual knowledge for students learning in matched and mismatched conditions. Learning performance in matched conditions was significantly higher than the one in mismatched conditions.

The common method for obtaining learning styles from the user is using some kind of questionnaire. There are specific questionnaires for each one of the learning style models, for example, Kolb's Learning Style Inventory [34]. Although this method enables a very reliable diagnosis of learning styles, filling out a questionnaire is usually boring and time-consuming for students. Researchers continuously seek for methods to infer student's learning style from her/his interaction with a system. One approach is using Bayesian networks, as implemented in SAVER [22] for detection of the Felder–Silverman learning style model. Graf and Kinshuk [24] proposed another approach, applicable to learning management systems in general instead to a single e-learning system. They have designed general patterns indicating user preferences for a learning style dimension and calculated the level of those dimensions on the basis of the patterns values.

Explicit detection of user learning styles is a quite difficult process, either for user to fill out the questionnaire, or for AES developers to design and implement dynamic detection of learning styles from user interaction. In order to simplify the learning styles identification process and to develop a more reliable user model, Graf, Lin and Kinshuk [25] investigated relationships between learning styles and cognitive abilities. They have identified connections between learning styles in the Felder-Silverman learning style model and the working memory capacity as an example of cognitive abilities. The learners with a low working memory capacity display an active, sensing, visual and global learning style, while the learners with a high working memory capacity tend to be reflective, intuitive and sequential. These results show that the identification process of both learning styles and cognitive abilities can be supported by each other, thus contributing to the user modelling process.

3.2 Previously Acquired Knowledge and Skills

The second broad category of user characteristics encompasses prior experience in using computers and Internet, previously acquired psycho-motor skills and background knowledge.

Experience. It is generally understood that prior experience in using computers is a good predictor of user performance [2, 3, 39]. Since the diffusion of Internet and growing number of systems delivered as web-based applications, the same claim stands for the experience in using hyperspace, as confirmed in [4, 20]. The experience in the usage of a concrete system is not included since it cannot be perceived as a previously acquired skill.

Psycho-motor skills. Early research suggested the importance of certain psycho-motor abilities, e.g. using the keyboard when using complex computer systems [3]. This is not so evident in recent research, probably due to the fact that the participants of most empirical studies are recruited from student population already familiar with computers. However, considering general population as potential target users of e-learning systems, this user characteristic becomes again an important variable that could influence the interaction. In addition to that, HCI research specifically considers users with limited psycho-motor skills such as disabled and elderly people. An example of information retrieval system adapted to these groups of users is AVANTI [19].

Background knowledge. This category is considered as two-sided. First, it refers to the user's knowledge related to the subject matter that is acquired prior to AES usage. Previously acquired knowledge is often functionally different from the knowledge to be attained in interaction with the system. Second, background knowledge encompasses prior experience in fundamental skills related to the subject, but acquired in a different context. For example, if user objective is a creation of a HTML page, then her/his HTML experience is considered as background knowledge. The relevance of background knowledge for adaptation is very well recognized in the HCI research and this variable is often implemented in AES's, *cf.* [7].

3.3 System Related User Characteristics

Goals and requirements. User goals and requirements (considered as short-term goals) are one of the main variables directing the adaptation in many adaptive and adaptable systems. In instructional systems, user goals usually depend on teaching strategies (and sometimes are even set by the system), so the techniques for adaptation to learning goals are various, see for example ELM-ART [56] for problem solving support, KBS Hyperbook [29] for project-based learning and INSPIRE [41] for a goal-driven approach.

Preferences. In general, every user has individual preferences related to the style of displaying information on screen. A user may prefer larger fonts, link annotation in different colours, coloured background, less information on the page, etc. However, user preferred styles of presentation modes are limited by the facilities of the system interface, so they can be considered as system dependent variables to some extent. User preferences are extremely hard to deduce by the system, so in most cases the user provides that information to the system, directly or indirectly. The preferences provided by the user are often a very reliable part of the user model [31]. Still, this is a changeable variable, which complicates the process of user modelling. Probably the most successful way of modelling preferences is enabling user customization of her/his user model, the way it is done in AHA! [12] or ELM-ART [56].

Interaction styles. Interaction styles in existing systems include menus, command entries, questions and answers dialogues, form-fills and spreadsheets, natural language dialogue and direct manipulation [44]. Each user may individually prefer a certain interaction style, but it is a general opinion that menus are more useful for novices than commands, because users do not have to remember much information. Conversely, commands are usually quicker and are preferred by experienced users [*ibid*]. Adaptation to user interaction styles is implemented for example in AKBB [27].

Motivation. The role of motivation in the learning process is generally acknowledged in educational psychology. Students with higher levels of intrinsic motivation and self-efficacy achieve better learning outcomes [43]. In a traditional classroom the teacher knows how to perceive the level of students' motivation, how to adapt his teaching strategies to the students' current motivational state and sometimes even how to increase their motivation for learning. However, in computer-assisted learning, the possibilities of exploiting motivation to improve learning performance are mainly neglected [58]. Recent studies make certain progress in this area. Specifically, Hurley and Weibelzahl [32] have developed a recommender tool, named MotSaRT, which suggests intervention strategies for teachers to increase student's motivation.

Intrinsic motivation is a rather personal user feature, mostly reflecting the user's desire and willingness to make an effort towards a specified goal. Still, it is very natural to consider motivation as a system dependent feature, for two reasons. First, to some extent the level of user motivation is dependent on the goal, and the goal is commonly defined by the system. Second, the means and manners of presenting the learning material can greatly affect user motivation. Thus, regarding the features of the system that form motivation (e.g. making the system visually attractive, well structured, highly usable and effective) designers can make significant progress in increasing the level of user motivation.

Expectations. User's previous interactions with the same or similar system often create expectations of system usage. If a user was satisfied in previous interactions, she/he will probably have positive attitude towards the system and expect a pleasant and beneficial session. A recent study showed that learners with greater expectations of e-learning have experienced higher levels of fulfilment in using e-learning systems, although they did not achieve higher learning outcomes [38]. Older reports confirming the influence of users' expectations on usage of interactive systems could be found in [3].

4 Framework Summary and Discussion

Summarizing the previous section, Table 1 gives a brief overview on the user individual characteristics exploited as user model variables of various adaptive and adaptable systems. The table is derived from eight survey papers and provides a comparison of researchers' acknowledgments of each particular variable as a source for adaptation.

The framework proposed in this paper and synthesized in the table has certain limitations regarding the first intention of this study, which was to consider only evaluated AES's, that is, precisely the studies that have confirmed adaptation success. However, studies on the evaluation of adaptive and adaptable systems are rarely conducted, unfortunately keeping track with the lack of empirical studies in the HCI field in general, cf. [11, 57]. Additionally, methods and approaches for evaluation of adaptive systems are still explored and not yet strongly established [59]. Consequently, the table also quotes a number of survey papers where an empirical confirmation of the influence of identified variables on learning process in non-adaptive learning systems is offered. It can be assumed that adaptation of the system to those user characteristics that significantly correlate with learning outcomes acquired in non-adaptive learning systems could bring substantial benefits to students' learning performance. Such variables could be then considered as relevant for adaptation.

A number of user individual characteristics seem to have been validly and reliably identified in the HCI literature, but the terminology used (the features names) and their precise relationships to each other is not always clear. That was the most significant practical difficulty that we faced in the attempt to suggest a set of relevant user characteristics. For example, identification of cognitive and learning styles from case studies was challenging due to interchangeable usage of these terms. Accordingly, in this paper cognitive styles are considered as information processing strategies in general, while term learning styles refer only to the user preferred learning strategies, as described in the previous section. Similar reasoning is applied when considering spatial ability. We have chosen to explain various dimensions of spatial ability instead of using different terms for different dimensions.

Table 1. User individual characteristics potentially relevant for adaptation

		Egan, 1988	Norcio & Stanley, 1989	Browne *et al.*, 1990.	Dillon & Watson, 1996	Brusilovsky, 2001	Rothrock *et al.*, 2002	Brusilovsky & Milan, 2007	Grimley & Riding, 2009
Personal characteristics and preferences	Age			•					
	Gender	•							•
	Cognitive abilities	•	•	•	•				•
	Personality			•			•		
	Cognitive style		•	•			•	•	•
	Learning style					•		•	
Previously acquired knowledge and abilities	Experience	•	•	•		•		•	
	Psycho-motor skills			•	•		•		
	Background knowledge	•	•			•		•	•
System related user characteristics	Goals and requirements			•		•	•	•	
	Preferences		•	•		•			
	Interaction styles		•						
	Motivation			•					
	Expectations			•					

It is important to take into account that some variables, although clearly identified, do not affect user interaction independently (e.g. age, experience and background knowledge) and they should be considered regarding their natural overlap with each other. Recent research suggests that relationships among variables in some cases could be exploited for simplifying user modelling process, e.g. the relationship between learning and styles and cognitive abilities [25, 28].

Relevant user individual characteristics, even when clearly identified and properly evaluated, certainly do not represent the sufficient set of variables to guarantee adaptation success. Some research emphasizes that user environment plays an important role in user interaction e.g. [4]. *Environment data* comprise all aspects of the user environment that do not directly translate to user characteristics, but may have an impact on user's goals and resources. A number of systems (for various purposes) are able to adapt to environment data (*ibid.*). It is also recognized that the adaptation to *groups of users* and to *user situation specificity* [47] is important. More recently, growing research on mobile and ubiquitous computing has expanded the notions of user environment and user situation specificity and has recognized the need of adapting to a broader *context of user's work*, including user platform, location, environment and a number of human dimensions [7].

Concerning all variables suggested in the framework, in addition to the ones mentioned above, the most often used trigger for adaptation is the user progress in system usage. In adaptive educational systems, *knowledge* is the best indicator of user status and commonly used variable to initiate adaptation, e.g. in ELM-ART [56], KBS Hyperbook [29], Interbook [5] and AHA! [50].

Many researchers disagree on the importance of modelling of some of user individual characteristics and about their usage for adaptation purposes, as shown in Table 1. Sometimes even the same authors over the years have recommended different set of user model attributes (compare [4] with [7]). Although Brusilovsky's six-category classification [*ibid*] is clear and applicable, the framework offered in this paper reflects human features which are classified into three broad "user-related" categories and then fine-grained into particular features which are appropriate as attributes for user model. Nevertheless, the framework is just a preliminary result of a comprehensive ongoing research. The field is emerging, thus it may be possible to include new user features over time. That is, research concerning affective state of the learner and its influence on interaction is innovative and promising (several approaches can be found in [37]).

The proposed framework represents the authors' perspective of the state-of-the-art in analyzing individual differences, and intends to serve as a staring point for AES's design/research teams. Respecting the fact that user performance considerably depends on a particular system, designers are encouraged to conduct their own user analysis concerning the system being developed, searching for the appropriate set of user model variables that will lead to the adaptation success. It is important to have an open mind in searching for user characteristics relevant for a particular system *cf.* [31], also taking into account the target users group. A subset of variables hypothetically relevant for a particular system and target user group could be selected and implemented. However, evaluation of system adaptation to these variables should follow the implementation to ensure that the adaptive system advances users' interactions. Initially selected set of hypothetical sources for adaptation can be refined through formative evaluation in any stage of the developing process. In addition, it is important not to consider each variable separately, but to find a combination of characteristics that would ensure a major benefit. The cost ratio issues of the adaptation should not be ignored. In that context, a preliminary assessment of the potentially relevant variables enabled by this survey can contribute in disregarding unnecessary variables and consequently decrease efforts and expenses of the developed system.

5 Conclusion and Future Work

This paper presents a survey on user individual differences employed in user modelling of adaptive learning systems. The set of user individual characteristics employed as sources for adaptation of e-learning systems was established and the framework for their categorisation is suggested. The identified characteristics are classified into three broad categories: personal user characteristics, previously acquired knowledge and skills as well as system related user characteristics. For each recognized variable, three significant aspects are addressed – its definition, implementation in existing systems and evaluation of its relevance for adaptation – whether in adaptive (where available), or non-adaptive learning systems. In addition, methods used for detection of described characteristics are reported and discussed.

Depending on the nature of the system being developed and the target user groups, this categorisation may be considered as an initial set of possible variables that can be embraced as candidate sources for adaptation. Careful evaluation of system's adaptive behaviour should reveal the combination of characteristics that will cause the biggest impact on both learning performance and satisfaction in system usage.

This framework represents an initial attempt to construct a set of user individual characteristics significant for system adaptation. Further research is needed to investigate successful methods and approaches for implementation of adaptive or adaptable behaviour to the identified characteristics, following the motto "do not diagnose what you cannot treat" [31]. The future research will include an in-depth analysis of existing adaptive systems, focusing on evaluated systems that provide effective and efficient adaptations.

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