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ANATOMY OF STUDENT MODELS IN ADAPTIVE LEARNING SYSTEMS: A SYSTEMATIC LITERATURE REVIEW OF INDIVIDUAL DIFFERENCES FROM 2001 TO 2013*

JELENA NAKIC

ANDRINA GRANIC

University of Split

VLADO GLAVINIC

University of Zagreb

ABSTRACT

This study brings an evidence-based review of user individual characteristics employed as sources of adaptation in recent adaptive learning systems. Twenty-two user individual characteristics were explored in a systematically designed search procedure, while 17 of them were identified as sources of adaptation in final selection. The content analysis of 98 selected publications that include evidence of adaptation efficiency is conducted. The quantitative representation of the findings shows current trends in the research of individual differences, as well as the tendencies of their further employment in student modeling. The article contributes to the body of knowledge on user individual differences and consequently to the research and development of adaptive learning systems. Additional contribution of the study is in-depth description of development and evaluation of the search strategy which

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makes the method easily replicable as well as suitable for modification and employment in systematic literature review in any research field.

A number of student's individual characteristics are involved in understanding and knowledge acquisition process, and the potential combinations of cognitive and non-cognitive characteristics that could considerably affect learning performance are countless (Jonassen & Grabowski, 1993). In web-based learning, where learning is commonly occurring without initiative and support of a teacher, student's individual characteristics have a more and more significant role and can even became a crucial factor of student's success or failure. Both the experts (researchers and developers) and the users (students and teachers) of learning systems agree that advanced learning systems should be adaptive, as reported by Harrigan, Kravčík, Steiner, and Wade (2009). Adaptive systems commonly implement dynamic adaptation on the basis of system assumptions about the user, inferred by monitoring user's interaction and stored in *user model* (Kobsa, 1995).

The study presented here offers a novel evidence-based solution to an initial question of adaptivity: to what these systems should be adapted, or what characteristics of the user should make a user model, in order to provide high learning achievement through a pleasant learning experience? Complementarily to many literature review studies that bring papers on theoretical approaches and frameworks that acknowledge the role of user individual differences but do not provide evidence on adaptation efficiency (e.g., Grimley & Riding, 2009; Thalmann, 2008; Vandewaetere, Desmet & Clarebout, 2011), this study aims to identify publications that bring successful stories of adaptation to various individual characteristics.

The origin as well as the incentive for the study is a framework for user individual differences potentially relevant for adaptation of learning systems (Granić & Nakić, 2010). The framework presented the-state-of-the-art in user individual differences and pointed out the fact that studies on the evaluation of adaptive learning systems are rarely reported. Due to the lack of evaluation studies on adaptive systems, the studies on influence of these variables on learning behavior and learning performance in non-adaptive systems were also considered to support the relevance of the variables. Therefore, in this wide area of individual differences in adaptive education, the need for systematic research on user characteristics adaptation to which actually contributes to learning performance and learning experience became a necessity. *Learning performance* refers to educational effectiveness regardless of different kinds of learning and learning achievements (*cf*. Grimley & Riding, 2009), while *learning experience* refers to user experience as defined in ISO FDIS 9241-210 but which occurs in learning settings, including both traditional learning as well as interaction with software applications.

In the growing area of web-based education, novel adaptive learning systems frequently introduce the new means of development and deployment of adaptive mechanisms into traditionally non-adaptive environments such as learning management systems, as well as into commonly adaptive learning facilities such as intelligent tutoring systems and adaptive hypermedia educational systems. In addition to that, advanced techniques of user modeling adopted from data mining and artificial intelligence (*cf.* Desmarais & de Baker, 2012) create new possibilities for automatic detection and dynamic adaptation of learning systems. Keeping track with recent findings in the field, it can be noticed that the structure of user models in adaptive systems goes through slight but constant changes over time. It is not surprising that even the same authors over the years recommend different sets of user model attributes (compare, for example Brusilovsky (1996, 2001) with Brusilovsky and Millan (2007). It is evident that researchers actually disagree on the importance of modeling some of user individual characteristics and about their usage for adaptation purposes (Granić & Nakić, 2010). Those constant changes in the field became an additional motivation for the research which aims to explore the efficiency and effectiveness of adapting a learning system to particular attribute.

Starting from the framework (Granić & Nakić, 2010) as an initial set of attributes and extending it with several user characteristics that were neglected for some time but actualized again, the set of 22 user model attributes was concluded. For each of the candidate variables, we have conducted a methodologically rigorous, comprehensive search and content analysis of literature from 2001 to nowadays. A systematic search strategy was built iteratively as proposed by Kitchenham and Charters (2007), while the step-by-step procedure for identifying the relevant body of literature was adjusted to meet the specific nature of the study. The method for content analysis of publications was developed by adopting a structured approach as suggested by Webster and Watson (2002). In the search procedure, 180 different publications were obtained while 98 publications were selected for the review. Following the concept-centric approach of structuring the literature review (Webster & Watson, 2002), a synthesis of obtained results is submitted in the form of quantitative and qualitative representation of actual usage of individual characteristics as attributes of user models in recent adaptive learning systems.

BACKGROUND TO THE RESEARCH

There are a number of user individual differences that seems to shape user interaction with any system in any domain. When we restrict our observation to the educational area, that number is not decreasing. On the contrary, whole new classes of characteristics attributing to learning process are emerging, such as learning styles, cognitive styles, and meta-cognitive abilities. At the same time, some of the traditionally important user characteristics are employed in an advanced manner to facilitate learning activities (Brusilovsky & Milan, 2007). The more significant role of individual traits such as learner cognition and affective state is recognized and acknowledged in recent web-based learning systems (Grimley & Riding, 2009; Tsianos, Germanakos, Lekkas, Mourlas, Belk, Christodoulou, et al., 2008). It becomes evident that the rapidly advancing area of web-based education fluently changes and reshapes the body of knowledge on learner individual differences.

Individual Differences in Adaptive Education: A Historical Perspective

The study presented here began with the systematic investigation of the following set of variables: age, gender, cognitive abilities (perceptual speed, processing speed, working memory capacity, reasoning ability, verbal ability, spatial ability and other cognitive abilities), meta-cognitive abilities, psychomotor skills, personality, anxiety, emotions and affect, cognitive styles, learning styles, experience, background knowledge, motivation, expectations, preferences, and interaction styles. Before explaining the method for investigation of the actual usage of these characteristics as attributes of user models in recent adaptive learning systems, the candidate variables are briefly presented and their so far known influence on learning behavior and learning performance is reported.

The *age* of a learner is usually related to his/her prior experience and background knowledge. However, there are differences in user performance (Egan, 1988), learning behavior (Ford & Chen, 2000), and preferences (Alepis & Virvou, 2006; Kallinen & Ravaja, 2005) related directly to age of the users. *Gender* is also related to learning behavior, as well as to motivation and learning outcomes (Ford & Chen, 2000; Grimley & Riding, 2009), although the studies that do not confirm the influence of gender can also be found (Munoz-Organero, Munoz-Merino, & Kloos, 2011).

Considering the role of learner cognition in web-based education, it appears that spatial ability is the most cited predictor of user performance, especially in the tasks that require complex navigation through hyperspace (Benyon & Murray, 1993; Chen, Czerwinski & Macredie, 2000; Juvina & van Oostendorp, 2006; Stanney & Salvendy, 1995; Zhang & Salvendy, 2001). *Spatial ability* is defined as the ability to perceive spatial patterns or to maintain orientation with respect to objects in space (Ekstrom, French, Harmon, & Dermen, et al., 1976), but is also denoted as the ability of mental manipulation of 2-dimensional and 3-dimensional figures, and sometimes as the ability of memorizing spatial arrangement of objects (Browne, Norman, & Rithes, 1990). Other cognitive abilities seem to have less influence in virtual learning environments in general. However, there are studies reporting impact on user interaction for *general intelligence* (Kelly & Tangney, 2006), *perceptual speed* (Dillon & Watson, 1996), *logical reasoning* (Dillon & Watson, 1996; Norcio & Stanley, 1989), *verbal ability* (Dillon & Watson, 1996), and *working memory capacity* (Graf, Lin, & Kinshuk, 2008; Grimley & Riding, 2009; Tsianos et al., 2008).

The importance of providing guidance on metacognition is also shifting from traditional learning to interactive learning environments. *Meta-cognitive abilities* include two cognitive components: knowledge on condition (i.e., conscious reflection on ones cognitive processes), and regulation on cognition (i.e., the ability of active control over cognitive performance; Brown, 1978). Research confirms that including a model of metacognition in interactive learning environments can improve students' interaction with the environment and contribute to their learning performance (Chi & VanLehn, 2010; Gama, 2004). Pioneer research suggested the influence of certain *psychomotor abilities* (e.g., using the keyboard on interaction with complex computer system; Browne et al., 1990). It appears that there are no recent studies regarding psychomotor abilities in e-learning systems; thus, this is another interesting subject for potential study.

Personality concerns user characteristics which remain stable over time and across situations: extraversion/introversion and neuroticism/emotional stability (Eysenck, 1992). These characteristics are considered as part of user individual traits that generally reflects on the way he/she uses a computer system (Browne et al., 1990; Brusilovsky, 2001; Lekkas, Germanakos, Tsianos, Mourlas, & Samaras, 2013; Rothrock, Koubek, Fuchs, Haas & Salvendy, 2002). User *affective state* is an integral part of his/her interaction with an application. It shapes user interaction and triggers his/her decisions even if it is not caused by the interaction. Still, this complex two-sided relationship is insufficiently explored and many adaptive learning systems do not acknowledge nor address user emotions. The impact of students' interaction with computer on students' emotion is explored, for example, in Alepis and Virvou (2006), Giovannella and Carcone (2011), and Moridis and Economides (2009), while the adaptation to user emotional states is provided in Lekkas et al., (2013) and Tsianos, Lekkas, Germanakos, Mourlas, and Samaras (2009).

The construct of *cognitive styles* is related to information processing patterns in general context. Some of the most exploited theories of cognitive styles in adaptive systems are field dependence/field independence (Witkin, Moore, Goodenough, & Cox, 1977), global/analytic cognitive style (Pask, 1976), and verbalizer/imager cognitive style (Riding & Buckle, 1990). User differences in cognitive styles result in different browsing strategies (Graff, 2005) and learning preferences (Chen & Macredie, 2002; Sadler-Smith & Riding, 1999). These differences in cognitive styles have been successfully employed in implementation of different instructional strategies in adaptive learning systems (e.g., Ford & Chen, 2000; Stash & De Bra, 2004; Triantafillou, Pomportsis & Demetriadis, 2003).

Contrary to cognitive styles, *learning styles* are related to learning environments only. Honey and Mumford (1992) define learning styles as "a description of the attitudes and behaviors which determine an individual's preferred way of learning." While there is a number of different learning style models, some of them are particularly embraced as sources of adaptation in adaptive learning systems, for example, Honey and Mumford's theory, as implemented in INSPIRE

(Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003), and Felder- Silverman learning style model (FSLSM; Felder & Silverman, 1988), as implemented in CS388 (Carver, Howard, & Lavelle, 1996), SAVER (Garcia, Amandi, Schiaffino, & Campo, 2006), an add-on for Moodle (Graf & Kinshuk, 2007), and LS-Plan (Limongelli, Sciarrone, Temperini, & Vaste, 2009). The initiative of providing adaptivity to learning styles comes from the assumption that matching the instructional strategy to learning styles of the learners leads to better learning performance. While there is a number of studies confirming this hypothesis, as reviewed by Akbulut and Cardak (2012), adaptation to learning styles still gets a lot of criticism supported by several null-results studies (Brown, Brailsford, Fisher, & Moore, 2009) and by questioning the methodology commonly used in confirmatory studies (Pashler, McDaniel, Rohrer, & Bjork, 2008).

It is generally understandable that *prior experience* in using computers is a good predictor of user performance (Benyon & Murray, 1993; Browne et al., 1990; Norcio & Stanley, 1989), along with experience in using hyperspace (Brusilovsky, 2001; Ford & Chen, 2000). *Background knowledge* or *prior knowledge* is another variable generally accepted as relevant for adaptation and often implemented in adaptive learning systems (*cf*. Brusilovsky & Milan, 2007). Background knowledge should be clearly distinguished from knowledge acquired in system usage, referred to as *current knowledge*, and often used as a trigger for adaptivity mechanisms in learning systems, for example in AHA! (De Bra & Calvi, 1998), ELM-ART (Weber & Brusilovsky, 2001), and INSPIRE (Papanikolaou et al., 2003). Current knowledge is considered as an indicator of learning status and it is a component of usage data rather than learner data (Brusilovsky, 2001), thus adaptation to current knowledge goes beyond the scope of the presented research.

Learner *motivation* is indisputably relevant for learning process, yet the possibilities of exploiting motivation in virtual learning environments are mainly neglected (Weibelzahl & Kelly, 2005). Novel research brings certain progress in the area, mainly in efforts of increasing learners' motivation (Brusilovsky, Sosnovsky & Yudelson, 2009; Hurley & Weibelzahl, 2007). User's previous interactions with the same or similar system often create *expectations* that could mediate the system usage (Browne et al., 1990; Nakić & Granić, 2009).

Every user has individual *preferences* related to the style or mode of displaying information on screen. Acknowledging the fact that the most reliable way of modeling preferences is direct input from the user (Hook, 2000), several adaptive learning systems successfully adapt to learners preferences, such as AHA! (De Bra & Calvi, 1998) and ELM-ART (Weber & Brusilovsky, 2001). *Interaction styles* in existing systems include menus, command entries, question and answer dialogues, form-fills and spreadsheets, natural language dialogue, and direct manipulation (Preece, Rogers, Sharp, Benyon, Holland, & Carey et al., 1994). In general, commands are usually quicker and are preferred by experienced users, while novice users usually prefer menus (Preece et al., 1994). Adaptation to user preferred interaction styles is implemented, for example, in AKBB (Granić, 2002).

These introductory reflections on user individual differences show that the research in adaptive education acknowledges a significant number of user characteristics which are involved in learning activities. It is evident that the role of several characteristics is very complex, since they could serve as predictors of learning performance as well as criterion of effective interaction, for example, learner's motivation and expectations. For several characteristics, advanced methods of automatic detection and quantification directly from interaction were developed, for example for cognitive styles (Jovanovic, Vukicevic, Milovanovic, & Minovic, 2012) and learning styles (Chang, Kao, Chu, & Chiu, 2009; Ozpolat & Akar, 2009), thus creating the possibilities for more accurate and reliable learner modeling, and consequently leading to more frequent and potentially more successful adaptation to these characteristics.

Related Work: The Respectable Reviews of Individual Differences

Brusilovsky and Milan (2007) reviewed user models of existing adaptive web-based systems in respect to the sources of adaptation and the techniques for user modeling. Their sources of adaptation regarding user individual characteristics are: user knowledge, interests, goals and tasks, background, and individual traits. Individual traits in this categorization include cognitive styles and leaning styles, while other individual traits, particularly cognitive abilities and personality, are marginally addressed. Several individual characteristics that are specifically important in learning environments, such as motivation, meta-cognitive abilities, and emotional factors, were not discussed. In the review of Thalmann (2008), the structured content analysis of 30 adaptive systems is reported. Ten systems were analyzed from each of the categories: adaptive education, adaptive information retrieval, and adaptive on-line information systems. As a result, a list of 13 "adaptation criteria" was completed, in which several user individual features are acknowledged: previous knowledge, preferences for specific content, mode of presentation and media types, as well as learning styles. Suggestions for the preparation of a learning material regarding the identified adaptation criteria are proposed, even without considering any cognitive abilities or cognitive styles. More consideration of individual differences, both theoretical and practical, can be found in the work of Grimley and Riding (2009). They concluded that cognitive style, gender, working memory, knowledge, and anxiety have significant impact on web-based learning. The effects of those variables on learning performance are discussed, along with potential interactions between variables and the effects of their interrelations on learning outcomes. Another contribution to the field is the work of Vandewaetere et al. (2011). In contrary to the three abovementioned papers written in the expert review manner, Vandewaetere et al. (2011) use rigorous method of literature selection as required for systematic literature review (Kitchenham, Brereton, Budgen, Turner, Bailey, & Linkmer, 2009). In comprehensive search for variables that are used as attributes of learner models in adaptive learning environments, they have reviewed 42 papers and classified them into 3 broad categories according to the sources of adaptive instruction, which can be (i) in learner as such, (ii) in the learner-environment interaction, or (iii) in their combination. The review encompasses 25 empirical studies and 1 experimental study, along with 15 theoretical proposals and 1 paper bringing both theoretical and empirical value. A more recent study of Chrysafiadi and Virvou (2013) brings an exhaustive survey of commonly used approaches to student modeling in existing adaptive learning systems. They classify sources of adaptation into: knowledge, errors and misconceptions, learning styles and preferences, cognitive aspects, affective features, motivation and meta-cognitive characteristics. A comparative analysis of student modeling approaches employed from 2002 up to 2007 with approaches prevalent from 2008 up to 2013 is conducted, and a discussion of the employment of these approaches in modeling respective student characteristics is provided.

Considering the benefits of adaptation to various learners' characteristics, research suggests that both adaptivity mechanisms and user modeling frameworks are insufficiently supported by empirical evaluation studies. The studies on the evaluation of adaptive systems are rarely conducted (Akbulut & Cardak, 2012; Vandewaetere et al., 2011), unfortunately keeping track with the lack of empirical studies in the Human-Computer Interaction (HCI) field in general (Chin, 2001; Weibelzahl, 2005). In addition, the results of evaluation studies are sometimes contradictory, as mentioned, for example, for learning styles. Conducted studies commonly depend on the learning environment and thus they are not suitable for generalization of findings. All of these factors are imposing the need for systematic review of individual differences in adaptive education, which has to be conducted according to the thoroughly designed method. In the next section, development of a thorough search strategy for major contributions is described and the search procedure is following.

METHOD

Following the guidelines for development and evaluation of the systematic literature review protocol as proposed by Kitchenham and Charters (2007), an iterative method for developing the search strategy was applied. An initial search strategy was conducted and then reappraised and refined in each step of the development process. Therefore the evaluation of the strategy is embedded in the iterative process of the strategy development. Kitchenham and Charters (2007) suggests that strategy development should be followed by conducting the review along the following steps: (i) identification of research in the literature, (ii) selection of primary studies, (iii) evaluation of the corpus with respect to the chosen quality parameters, (iv) extraction of relevant data, and (v) data synthesis. To address the complexity of identification of major contributions for this review, several inclusion and exclusion criteria are needed to be adopted. Accordingly, the adopted approach was slightly modified and a 6-step procedure was designed. In the next subsections, the iterative development of the search strategy is presented while the search performance through the 6-step procedure is following.

Search Strategy

In order to identify major contributions in leading journals and conference proceedings, a literature search was undertaken in the Science Citation Index Expanded (SCIE) and Social Sciences Citation Index (SSCI) using the service Web of Science. The search was limited from 2001 to 2014. A set of search keywords was used to search the topic fields (title, abstract, and keywords) of publications indexed in the Web of Science Core Collection. The search phrase was composed from four fragments joined with an AND operator. The first fragment keywords are related to adaptivity, intended to cover both adaptive and adaptable systems. In case these terms do not occur in the topics of the respective papers, we have included the notion of personalization, so the term (adapt* OR personali*) was used as the first fragment of the search phrase. To cover the field of educational systems, the second fragment of the search phrase was composed as follows: (education* OR e-learning OR web-based learning OR instruction* OR course*). In order to avoid the papers describing frameworks which are not evaluated or even implemented, we have restricted the search on papers reporting evaluation so the search term (evaluat* OR empiric* OR experiment*) was used as the third fragment. It has to be noted that these terms were not initially set in these forms but afterwards, during the search queries development process, as described later in this subsection.

In order to have a unique method for all user individual characteristics, we aimed to establish a query that would be suitable for each variable, meaning having the same first, second, and third part of the search phrase, and to differ only in the fourth part of the phrase since that part addresses different user characteristics. In order to find such a query, several search pilots were launched with the approximate terms for the first, second, and third part of the phrases and some concrete variables in the fourth part of the search phrase. Learning styles, cognitive styles, and background knowledge are used as representatives of the variables regarding the learning context, while age and gender were used to confirm the search efficiency for general user characteristics ensuring that search results do not have many items concerning general context, but are kept in the field of e-learning. Finally, the unique query was established in which the first three fragments were formed as stated at the beginning of this subsection and joined with an AND operator: (adapt* OR personali*) AND (education* OR “e-learning” OR “web-based learning” OR instruction* OR course*) AND (evaluat* OR empiric* OR experiment*), along with the fourth fragment which was fused to address the concrete variable. Using the final form of the search phrase, the search for all testing variables (learning styles, cognitive styles, background knowledge, age, and gender) was repeated to obtain the complete set of targeted publications. The process of search strategy development is summarized in Figure 1. Upon confirmation of the search strategy, the search for the rest of the variables was conducted.

Search and Refinement Procedure

For each of 22 variables of interest (stated in the background section), the search was performed and the list of results was analyzed and refined where needed. This procedure was conducted in the following 6-step procedure.

Step 1. Performing the Search

For each variable, the search was performed using the corresponding search phrase. The fourth fragments of the search phrases for pursuing those variables are introduced in Table 1. For example, Figure 2, in the set #16, presents the complete search phrase for background knowledge along with the number of results.

Step 2. Refining the Search Results List

For most of the variables the search results list contained a large number of papers and needed to be additionally filtered to select the publications that meet the purpose of this review. The commonly used filter was "Refined by: Research Areas = (COMPUTER SCIENCE OR EDUCATION EDUCATIONAL RESEARCH)", for example, for anxiety, preferences, expectations, and others. Figure 2 in set #17 shows the criterion for refining the search results list and presents the number of results after refining. In some cases, obtained results had a lot of papers dealing with education in general, so it was necessary to use a stronger filter. Thus, instead of the above mentioned filter, the filter: "Refined by:

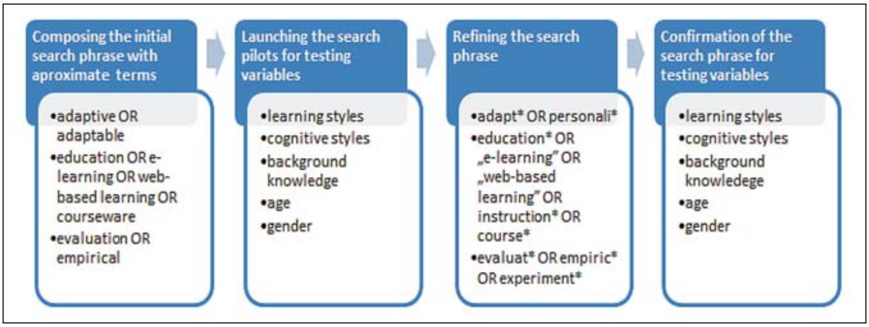

Figure 1. The iterative development of the search strategy.

Table 1. Step-by-Step Search Procedure and the Number of Results

Variable	AND Topic = (4th fragment keyword(s))	Accepted/ Prediction only	Times cited
Age	“age”	6	16
Gender	“gender”	9	51
Perceptual speed	perceptual	0	0
Processing speed	“speed of processing” OR “processing speed”	2	2
Working memory capacity	“working memory” OR “short-term memory”	6	64
Reasoning ability	“reasoning abilit*: OR “reasoning skill*”	1	3
Verbal ability	“verbal abilit*” OR “verbal intelligence” OR “verbal/linguistic intelligence”	0	0
Spatial ability	“spatial abilit*” OR “spatial intelligence” OR “visual* abilit*” OR “visual* intelligence” OR “spatial-visual*”	2	7
Cognitive abilities (other)	“cognitive abilit*”	6	149
Meta-cognitive abilities	meta-cognitive OR metacognitive OR “self-awareness” OR “self-monitoring” OR “self-regulation” OR “emotion-regulation” OR “self-explanation” OR “self-assessment”	8	36
Psychomotor skills	“motor skill*” OR “motor abilit*” OR “motor behavior*” OR “psychomotor skill*” OR “psychomotor abilit*” OR “psychomotor behavior*”	0	0
Personality	personality OR introver* OR extrover* OR extraver*	6	133
Anxiety	anxiety	4	42
Emotions and affect	emotion* OR affect*	5/2	6
Cognitive styles	“cognitive style*”	15	177
Learning styles	AND Topic = (”learning style*”) NOT Topic=(”cognitive style*”)	28/5	380
Experience	“prior experience” OR “previous experience” OR “computer experience” OR “computer knowledge” OR “computer literacy”	6	76
Background knowledge	“background knowledge” OR “prior knowledge” OR “previous knowledge”	16	38
Motivation	motivation*	10/6	52
Expectations	expectation*	2	24
Preferences	preferences	14	67
Interaction styles	“interaction style*”	0	0

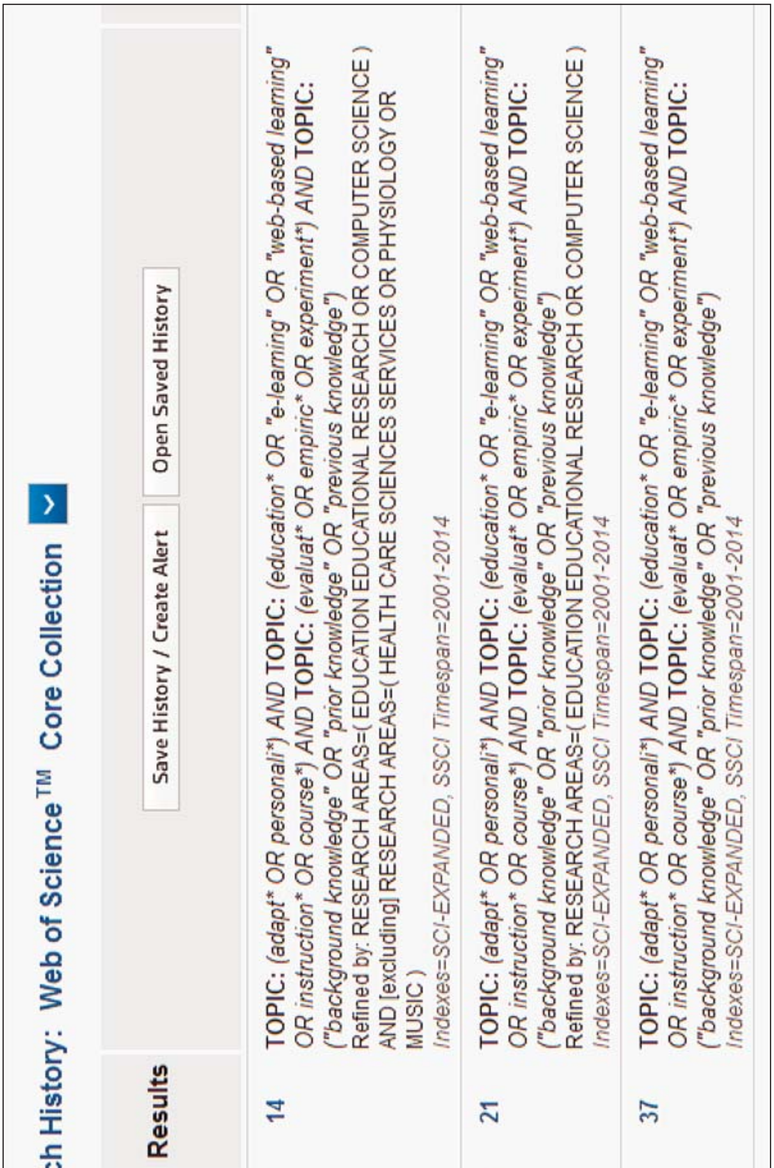

Figure 2. Saved search for background knowledge in Web of Science Core Collection.

Research Areas = (COMPUTER SCIENCE)" was used for age, emotions and affect, as well as for motivation.

Step 3. Excluding the Research Areas

Additional filtering was required to exclude the publications in those research areas that are not relevant for our purpose. For example, the exclusion criterion for background knowledge is presented in Figure 2, in set #18. The same exclusion criterion was applied to the majority of variables, that is, all research areas except COMPUTER SCIENCE and EDUCATION EDUCATIONAL RESEARCH were excluded from the search results list. For results lists having less than 8 items after refining, the excluding step was skipped.

Step 4. Selection by Title

The list of results obtained after exclusion was browsed to inspect the titles of the papers and eliminate the items that obviously do not belong in the scope of the research. In this step several review articles were excluded from the results list.

Step 5. Selection by Abstracts and Full Texts

For the rest of the papers, abstracts were read and the full texts were inspected where available. In total, there were 180 different abstracts out of 207 resulting papers, of which there were 51 different full texts out of 64 resulting full texts that were available to the authors. These 180 abstracts were read and 51 full texts were thoroughly inspected. In this step, the papers that mention a particular variable in theoretical or general context were identified and eliminated from the study. Notes were taken while reading, with special attention to studies which appeared to use more than one variable as a source of adaptation. In addition to that, several situations occurred when the results list for a variable does not address the particular variable, but address some of the other variables as sources of adaptation. These situations were carefully noted to be used in the next step.

Step 6. Backwards Checking

After reading all available accepted material for current variable, the check was made in the annotated bibliography of previously done variables to find the additional publications that address current variable but did not appear in the list of results. Such papers were manually added to the results list of the current variable.

To sum up, 98 publications were accepted for this review, 43 on the basis of full texts inspection and 55 on the basis of abstracts consideration. The searches were performed in November and December 2013, and the final check was conducted on January 21, 2014. To keep the results up-to-date, weekly e-mail alerting was activated about new entries for each of the saved searches.

RESULTS

All selected publications were collected in a single table ensuring that every title appears only once. The structure of the table is concept-centric rather then author-centric (Webster & Watson, 2002), meaning that the list of identified papers is organized into sections according to variables which have been used as sources of adaptation in respective systems. For systems that address more than one variable as sources of adaptation, the primary variable, meaning the variable for which the system adaptation is the most successful, is identified. The paper is assigned to the primary variable section, while all sources of the system adaptation are listed in the last column of the table. For each paper, the main focus of the research is described and the influence of variable(s) is briefly reported. Thus, the table of results is actually an annotated bibliography of individual differences in adaptive education based on SCIE and SSCI databases. The reports of null evidence of adaptation efficiency are also accepted in this review, and respective variables are additionally annotated in the last column of the bibliography. Some of the highly cited papers from the annotated bibliography are extracted and presented in Table 2 at the end of this section. The structure of the Table 2 is following the structure of annotated bibliography, while the content of the Table 2 will be discussed later, previously to the presentation of the table.

Most of the reviewed papers describe adaptivity features of adaptive learning systems, with or without inferring mechanisms for dynamic detection and prediction of user individual characteristics. However, there are several publications dealing only with prediction of user characteristics (e.g., learning styles), or examination of the factors that affect certain characteristics, such as motivation and emotions of learners while using an adaptive learning system. Considering the contribution of these publications to the significance of respective variables, they are also included in this review and their number is evident in Table 1.

For each accepted publication, the number of citations in the Web of Science Core Collection is extracted. For additional analysis of the variables' significance, a citations report on each variable results list was built and the number of citations for each variable is provided in Table 1. Additionally, the number of published items in each year and the number of citations in Web of Science Core Collection in each year are extracted from the reports. For each variable, the sum of published items per year and the sum of citations per year are calculated. Results are presented as relevant timelines in Figure 3 and Figure 4 respectively.

A total number of accepted publications for each variable is presented in Table 1. The most frequently used variable for adaptation is learning styles, appearing in 28 (27.6%) out of 98 publications. The second most frequently used variable is background knowledge (16.3%), while cognitive styles (15.3%) and preferences (14.3%) are following. Motivation is considered as a source of adaptation in 10 publications (10.2%). Six of these 10 papers also consider motivation as a criterion of learning success and propose various methods for increasing learner motivation while using

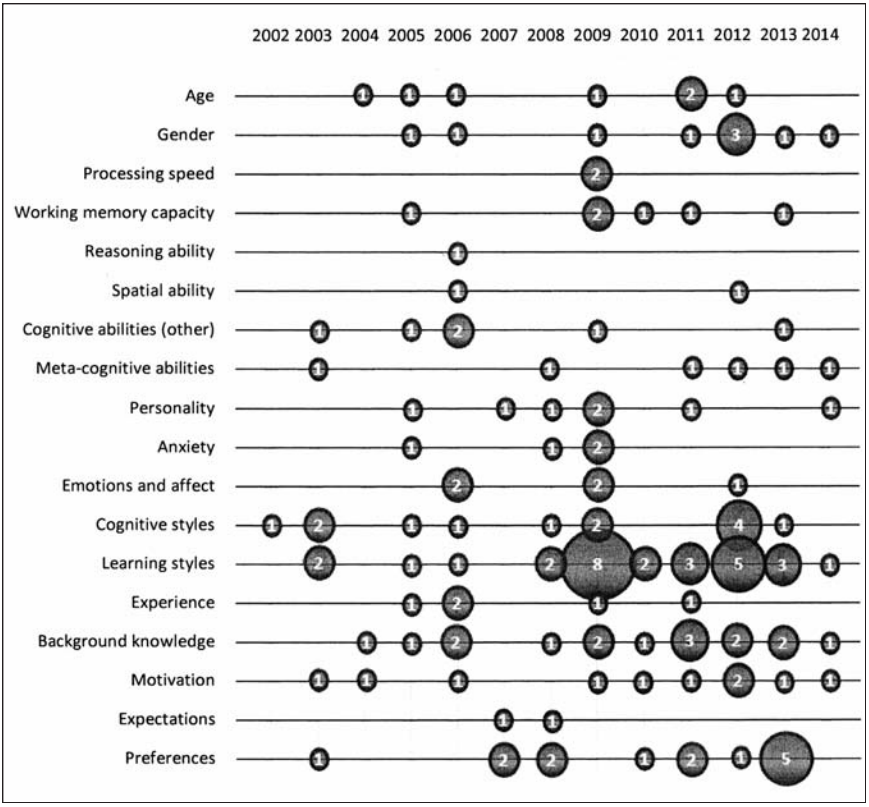

Figure 3. Published items timeline according to citations reports in Web of Science Core Collection.

respective learning environment. In addition, learning systems are often adapting to students' cognitive abilities, gender and metacognitive abilities, and less frequently to age, working memory, personality, previous experience and levels of anxiety. The adaptation to several learner characteristics is often found, for example, in Germanakos, Tsianos, Lekkas, Mourlas, and Samaras (2009), Johnson (2005), McNulty, Sonntag, and Sinacore (2009), Melis, Haywood, and Smith (2006). A number of systems implement adaptivity to user progress or currently achieved knowledge level along with adaptation to other learner characteristics, such as learning styles (Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011; Papanikolaou et al, 2003; Sampayo-Vargas, Cope, He, & Graeme, 2013), preferences (Acampora, Gaeta & Loia, 2010; Gogoulou, Gouli, Grigoriadou, Samarakou & Chinou, 2007; Medina-Medina, Molina-Ortiz, & Garcia-Cabrera, 2011), etc.

According to the number of accepted publications in Table 1, it appears that several individual differences are not included as attributes of user models in

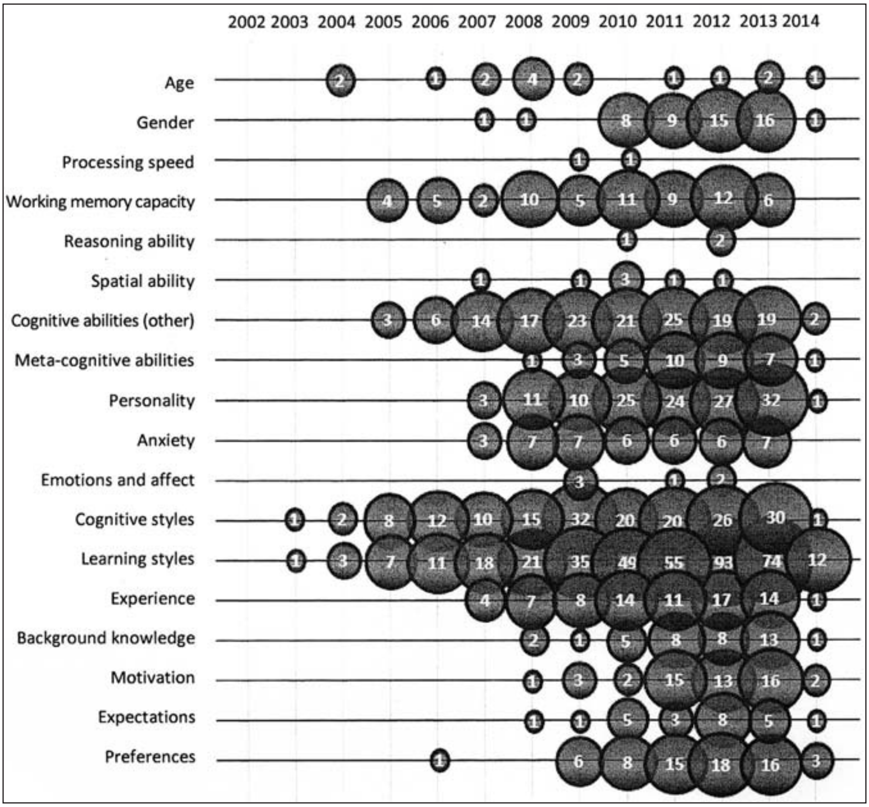

Figure 4. Citations timeline according to citations reports in Web of Science Core Collection.

recent adaptive learning systems, namely perceptual speed, verbal ability, psychomotor skills, and preferred interaction styles. These findings suggest that there is no need to adapt an interactive learning environment to these characteristics, at least for environments which intend to serve for general population of students. Designing learning environments for disabled learners may consider some of these characteristics, in respect to the nature and severity of their disability. These issues require further investigation which is out of the scope of this review.

Figure 3 and Figure 4 are revealing the tendencies in structuring the student models of adaptive learning systems. Although they present the appearance of respective publication only in two bibliographic databases, namely SCIE and SSCI, they still illustrate the enormous progress in the research on individual differences in adaptive education of the 21st century. While in 2001 there are no papers meeting the search criteria in selected databases, 28 papers are published from 2002 up to 2007, and 70 papers from 2008 up to now (mainly to the end of 2013 since the search was finished on January 21, 2014).

Figure 4 reveals individual characteristics that have attracted the highest interest of researchers in the last 14 years, including the beginning of 2014. According to the number of citations, the most prevalent characteristic is still learning styles, while cognitive styles, cognitive abilities, and personality are following. According to the ratio of the number of citations and published items, it appears that cognitive abilities (24.83) and personality (22.17) are the most appealing characteristics to researchers and that their role in adaptive education is still insufficiently explored.

Comparative analysis of findings in relation to user characteristics identified in adaptive hypermedia systems by Brusilovsky up to 2001 (Brusilovsky, 2001) confirms that student background knowledge, experience in using computer and Internet, preferences and individual traits are still important attributes of user models in adaptive learning systems. On the other hand, after 2001 several new attributes occur more frequently, such as emotional, motivational and meta-cognitive factors which are specifically important in learning activities.

Considering the involvement of selected papers in journals and books/conference proceedings, we found that 28 articles (28.6% of all accepted papers) are published in *Computers & Education* journal. The second most significant journal is *Educational Technology & Society* with 7 articles, followed by *IEEE Transactions on Learning Technologies* and *Lecture Notes in Computer Science* series with 6 publications each. Four papers are found in *Interacting with Computers* which makes this journal the only resource from the HCI field in top five journals of our list of results. The rest of the journal list is consisted of 23 resources mainly coming from educational and educational technology research areas.

Acknowledging the number of citations per year as a measure of influence of scientific publications, several highly cited papers are selected from the annotated bibliography of this review and presented in Table 2. The sources of adaptation are certainly not the only cause of high number of citations of these papers, but the number of citations per year, along with the number of published items per year, is probably the most illustrative indicator on variable impact in the respective scientific field. An additional criterion for inclusion of publications in Table 2 was the usage of multiple variables as sources of adaptation. The publications presented in Table 2 are among the most respectable articles on adaptive learning systems. They often bring the methods of modeling respective student model attributes along with the description of systems' adaptivity mechanisms. Due to the applied search method, the evaluation studies of systems' adaptive behavior efficiency are included in these publications.

DISCUSSION

The presented research is comparable with related work. More specifically, the study is similar to Thalmann's (2008) in terms of quantitative interpretation of the

Table 2. The Most Relevant Publications Employing Particular Variables as Sources of Adaptation.

Author(s) / Journal or Book / Citations in WoS	*Title*	*Main focus*	*Variable(s) influence*	*Source(s) of adaptation*
AGE				
(Kabassi & Virvou, 2004) / INTERACTING WITH COMPUTERS / 12	Personalised adult e-training on computer use based on multiple attribute decision making	How a multiple attribute decision making method, the Simple Additive Weighting (SAW), is used in Web-IT. Several attributes are identified that the system should take into account in making decisions about the learning process.	Importance of an attribute depends on learner's age. The generation of advice is based on stereotype user modeling according to age.	age
GENDER				
(McNulty, Sonntag, & Sinacore, 2009) / ANATOMICAL SCIENCES EDUCATION / 39	Evaluation of Computer-Aided Instruction in a Gross Anatomy Course: A Six-year Study	Effectiveness of Computer-Aided Instruction (CAI) and the factors affecting level of individual use are reported. Three CAI applications were tested that differed in specificity of applicability to the curriculum and in the level of student interaction with the CAI. The results were obtained by combining server statistics with student surveys.	Significant differences were found in usage frequencies for specific types of CAI when comparing the students' gender, personality preferences (two dimensions of MBTI) as well as Kolb's learning styles (Convergers vs. Assimilators).The score on exams is related to the level of CAI utilization. No correlation is found between experience ("computer literacy") and CAI utilization.	gender, personality, learning styles, experience[a]
SPEED OF PROCESSING				
(Germanakos, Tsianos, Lekkas, Mourlas, & Samaras, 2009) / COMPUTER JOURNAL / 1	Realizing Comprehensive User Profile as the Core Element of Adaptive and Personalized Communication Environments and Systems	User perceptual preferences as part of a comprehensive user profile for adaptivity of general purpose web content. Describes a number of intrinsic user characteristics that contribute to user profiles. Further emphasis the relevance of these characteristics for web personalization. The architecture of the AdaptiveWeb system is presented along with the method for user profile construction as well as the preliminary evaluation results.	The significant influence of cognitive styles (Riding's typology), cognitive processing speed efficiency, and emotional processing on users' learning performance was found. Some effect of working memory was demonstrated: in conditions where users with low working memory received segmented content, they perform equally well as the users with high working memory.	speed of processing, wm capacity, anxiety, emotions; cog. styles
WORKING MEMORY CAPACITY				
(Kalyuga & Sweller, 2005) / EDU TECH RESEARCH AND DEVELOPMENT / 59	Rapid dynamic assessment of expertise to improve the efficiency of adaptive e-learning	The paper proposes a method of evaluating learner expertise based on assessment of the content of working memory and the extent to which cognitive load has been reduced by knowledge retrieved from long-term memory.	Adaptive instruction was dynamically tailored to changing levels of expertise of the learners using rapid tests of knowledge combined with measures of cognitive load. Results show that adaptive instruction contributes to higher knowledge and cognitive efficiency gains of the learners.	working memory capacity
(Loboda & Brusilovsky, 2010) / UMUAI / 2	User-adaptive explanatory program visualization: evaluation and insights from eye movements	An attempt to assess the value of user-adaptive visualization and explanatory visualization in learning programming is proposed. The findings of the study show that explanatory visualization increases the understanding of a new programming topic.	Adaptive visualization holds students' attention more than equivalent non-adaptive application. The results suggest that working memory span can mediate the perception of adaptation.	working memory capacity
SPATIAL ABILITY				
(Wang, Li, & Chang, 2006) / INTERACTING WITH COMPUTERS / 7	A web-based tutoring system with styles-matching strategy for spatial geometric transformation	A traits-based personalization of learning experience in CooTutor. It is shown how the learners with different degrees of spatial reasoning skills and learning styles can then be tutored adaptively. Students with higher spatial ability are provided with less degree of visualization. Adaptivity mechanisms are developed to achieve matching to sensing/intuitive and active/reflective dimensions of FSLSM.	For most of the students the spatial-visualization ability is increased after using the CooTutor. It is concluded that adaptive material selection fulfilling styles matching strategy does not outperform typical one-size-fits-all designs, but the situation of styles mismatching may have negative effects on learning, specifically for learners with extreme learning styles.	spatial ability, learning styles
COGNITIVE ABILITIES (OTHER)				

(Chen, Lee & Chen, 2005) / COMPUTERS & EDUCATION / 98	Personalized e-learning system using item response theory	A personalized e-learning system based on Item Response Theory. The system provides individual learning paths that can be adapted to various levels of difficulty of course materials and various abilities of students. Personalized learning guidance is aimed to reduce students' disorientation and cognitive overload.	Experimental results confirm that the proposed system increases learning efficiency and effectiveness. On the basis of subjective rating of students, the course material recommended by the system is highly appropriate and the students' satisfaction in using the system is very high.	cognitive abilities
META-COGNITIVE ABILITIES				
(Huang & Yhang, 2009) / COMPUTERS & EDUCATION / 15	Designing a semantic bliki system to support different types of knowledge and adaptive learning	Novel social software called "bliki" is proposed. The system combines the advantages of blogs and wikis using semantic web technology. The learners are able to arrange personalized learning goals and paths according to their metacognitive knowledge and collaborative activities.	The results obtained in empirical study show that this system is able to support various types of knowledge and to improve learning performance.	meta-cognitive abilities
PERSONALITY				
(Cho, Gay, Davidson & Ingraffea, 2007) / COMPUTERS & EDUCATION / 54	Social networks, communication styles, and learning performance in a CSCL community	An empirical investigation of the relationships between communication styles, social networks, and learning performance in a computer-supported collaborative learning (CSCL) community. The study employed social network analysis (SNA) and longitudinal survey data.	Students' communication styles and pre-existing friendship network significantly affect the way they build their social networks for collaborative learning. Compared to students who were on peripheral positions of the network, the students who were in the center of the network achieved higher learning outcomes.	personality
(Johnson, 2005) / INT JNAL OF HUMAN-COMPUTER STUDIES / 25	An empirical investigation of sources of application-specific computer-self-efficacy and mediators of the efficacy - performance relationship	A validation of a model of four factors that contribute to application-specific computer self-efficacy (AS-CSE) formation (previous experience, personality, learning goal orientation and computer anxiety) and three factors that mediate the relationship between AS-CSE and performance (goal level, goal commitment and performance goal orientation).	Evaluation shows that experience, trainee personality and learning goal orientation were positively related to AS-CSE, while computer anxiety was negatively related to AS-CSE.	personality, experience, anxiety, metacognitive abilities
ANXIETY				
(Solimeno, Mebane, Tomai, & Francescato, 2008) / COMPUTERS & EDUCATION / 15	The influence of students and teachers characteristics on the efficacy of face-to-face and computer supported collaborative learning	E-learning, when integrated with computer supported collaborative learning, may provide high quality education. The connections of students' personality characteristicsand learning strategies as well as teachers' characteristics with better learning outcomes in online or face-to-face contexts are explored. Students who perform better online and face-to-face differ to some extent in their personality traits (measured by Big Five) and learning strategies, but their differences do not correlate with learning outcomes.	It appears that online learning bring benefits to students who lack perseverance, are not very anxious, can control their emotional reactions and have external locus of control and high problem solving efficacy. Face-to -face collaborative contexts are found supportive to students who are less friendly, who do not want to collaborate with others, but are very conscientious and able to self-regulate their study schedules.	personality, anxiety, meta-cognitive abilities
EMOTIONS AND AFFECT				
(Chen & Sun, 2012) / COMPUTERS & EDUCATION / 3	Assessing the effects of different multimedia materials on emotions and learning performance for visual and verbal style learners	Relationships between emotions, learning performance and multimedia for students with verbal and visual cognitive styles. Static text and image-based multimedia material, video-based multimedia material, and animated interactive multimedia material, were presented to verbalizers and visualizers. The percentages of positive and negative emotions are computed from the coherence value, the accumulated coherence score and heart rate artefacts detected by the emWave system.	Video-based multimedia material generated the most positive emotion for verbalizers; while static text and image-based multimedia material and animated interactive multimedia material generated the more negative emotions in learners. The study partially supports the view that emotions directly affect learning performance.	emotions, cognitive styles
COGNITIVE STYLES				
(Cook, 2005) / ACADEMIC MEDICINE / 47	Learning and cognitive styles in Web-based learning: Theory, evidence, and application	A comprehensive literature search of medical and non-medical resources was conducted. The results show that cognitive and learning styles are dominant basis for adaptation of web-based learning systems.	The evidence of aptitude-treatment interactions is clear for the wholist-analitic construct and limited for the active-reflective construct. No evidence supports adaptivity to learners with concrete-abstract and verbal-imager cognitive styles.	cognitive styles

Table 2. (Cont'd.)

(Triantafillou, Pomportsis, & Demetriadis, 2003) / COMPUTERS & EDUCATION / 54	The design and the formative evaluation of an adaptive educational system based on cognitive styles	Discussion on design issues that were reported in literature on development of adaptive educational systems. The development of the AES-CS system based on student cognitive styles is described along with the recommendations of formative evaluation that was continuously conducted to control and guide the design process.	The students were satisfied with the initial adaptation to their cognitive styles in regards to field-dependent and field-independent dimension. The high level of the system flexibility and controllability was perceived as very important and useful for students.	cognitive styles
(Lo, Chan, & Yeh, 2012) / COMPUTERS & EDUCATION / 7	Designing an adaptive web-based learning system based on students' cognitive styles identified online	An adaptive web-based learning system focusing on students' cognitive styles (MBTI) with a mechanism to unobtrusively identify students' cognitive styles. The student model identifies students' cognitive styles based on their browsing behaviors through a multi-layer feed-forward neural network. The adaptation model presents adaptive web interfaces based on the cognitive style identified in the user model.	Results indicate that the proposed system could have significant impacts on students' engagement in learning measured by the average time that students spend reading the content pages. It seems that adaptive web-based learning system with dynamically identifying students' cognitive styles is equally effective as the system using cognitive styles known before browsing,	cognitive styles
LEARNING STYLES				
(Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003) / UMUAI / 102	Personalizing the interaction in a Web-based educational hypermedia system: the case of INSPIRE	INSPIRE adapts to learning styles (according to Honey and Mumford) and current knowledge level of the students. The system employs several adaptive presentation and adaptive navigation support techniques thus balancing between students' navigation freedom and system guidance. The system maintains the fully open learner model, enabling the learners to intervene in the adaptivity mechanism.	Comparing the navigation patterns of students (activists and theorists), the differences in learning behavior are found. According to subjective criteria, the learners generally appreciate the combination of the adaptivity techniques and the support offered by the system, but they also prefer the high level of learner control over the system functionality.	learning styles
(Klasnja-Milicevic, Vesin, Ivanovic, & Budimac, 2011) / COMPUTERS & EDUCATION / 22	E-Learning personalization based on hybrid recommendation strategy and learning style identification	A recommendation module of Protus is presented. Protus deploys an open learner model based on learning styles (FSLSM) and current knowledge state. Protus form the clusters of students on the basis of their learning styles. The system monitors students' learning behavior and discover patterns for each student. Finally, a recommendation engine produces the list of actions and recourses in the next session.	Learners who were using Protus continuously completed more lessons successfully than the students who were learning without recommendations. Subjective evaluation of the system showed high level of students' satisfaction with the recommendations convenience, speed and accuracy of the selection of appropriate learning objects and presentation methods.	learning styles, preferences
(Schiaffino, Garcia, & Amandi, 2008) / COMPUTERS & EDUCATION / 33	eTeacher: Providing personalized assistance to e-learning students	An intelligent agent, named eTeacher, is presented. eTeacher provides personalized recommendations to students who are taking courses through an e-learning system SAVER. The assistance is provided dynamically and based on students' learning styles (in respect to FSLSM, without visual/verbal dimension) and user progress through the course.	The precision of eTeacher obtained by analyzing students' log files (e.g. the percent of students who received positive feedback) is 83% of the total number of assistance actions. According to subjective students' satisfaction measure, the usefulness of the agent is 70%.	learning styles
(Tseng, Chu, Hwang, & Tsai, 2008) / COMPUTERS & EDUCATION / 30	Development of an adaptive learning system with two sources of personalization information	An adaptive learning platform, TSAL, which takes learning styles (based on the Keefe's approach) and individual learning behaviors (current knowledge state, learning effectiveness and the level of concentration) as sources for personalization.	The empirical results show that providing adaptive subject material along with adaptive presentation styles increases learning achievements and learning efficiency.	learning styles
EXPERIENCE				
(Leslie et al., 2006) / COMPUTERS IN BIOLOGY AND MEDICINE / 12	Clinical decision support software for management of chronic heart failure: Development and evaluation	The research objective is to develop and evaluate clinical decision support software to aid physicians treat patients with chronic heart failure. Evaluation included an editorial check, one-to-one interviews with potential users and educational meetings with general practitioners, junior doctors and medical students.	General practitioners scored significantly lower in computer literacy than junior doctors and medical students. Using the clinical decision support software, junior doctors and medical students have achieved higher performance than general practitioners.	experience
BACKGROUND KNOWLEDGE				
(Huang, Lin, & Huang, 2012) /	What type of learning style leads to online participation in the mixed-mode e-learning	The empirical study was conducted over a large sample of undergraduate students. FSLSM was used to explore the effect of learning styles in an online environment. The study investigates the mediating processes in the	Sensory students have a higher level of online participation and better learning performance. Intuitive learners showed lower level of online participation, while other dimensions of FSLSM showed	learning styles, background knowledge

COMPUTERS & EDUCATION / 7	environment? A study of software usage instruction	relationship between learning styles and e-learning performance and the moderating effects of prior knowledge.	no correlation. Prior knowledge partially moderates the relationship between online participation and learning performance.	
(Hsu, Hwang, & Chang, 2013) / COMPUTERS & EDUCATION / 2	A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students	A personalized mobile language learning system that includes (i) a recommendation mechanism that meet their preferences and reading proficiency levels and (ii) a reading annotation module that enables students to take notes of English vocabulary translations in different contexts on mobile devices during the learning process.	It is concluded that the personalized mobile learning approach assisted by translation annotation had a significant impact on reducing students' cognitive loads during the learning activity and consequently led to significantly better reading comprehension.	preferences, background knowledge (reading proficiency)
MOTIVATION				
(Chu, Hwang, Tsai, & Tseng, 2010) / COMPUTERS & EDUCATION / 29	A two-tier test approach to developing location-aware mobile learning systems for natural science courses	A mobile learning system that employs Radio Frequency Identification technology to detect the learning behaviors of students and provide personalized learning guidance (called two-tier test guiding). The developed system has been applied to a learning activity of a natural science course in an elementary school.	The experiment confirmed that learning with two-tier test guiding, compared to learning in a "pure" (tour-based) environment, promotes learning attitude (e.g. enhance motivation to learn), and improves the learning achievements of students	motivation (the impact of new approach on motivation)
(van Seters, Ossevoort, Tramper, & Goedhart, 2012) / COMPUTERS & EDUCATION / 2	The influence of student characteristics on the use of adaptive e-learning material	How individual characteristics of the students (prior knowledge, study level, gender and intrinsic motivation.) influence their learning paths and the learning strategies while learning with adaptive e-learning material. The study was conducted in context of a system named Proteus, which provides adaptive feedback to the students while doing exercises.	The self-reported learning strategies were correlated with the prior knowledge and intrinsic motivation of students. The level of study (BSc and MSc) is related to intrinsic motivation, learning paths and learning strategies.	age, gender[a], background knowledge, motivation
EXPECTATIONS				
(Shih, 2008) / COMPUTERS & EDUCATION / 15	Using a cognition-motivation-control view to assess the adoption intention for Web-based learning	Integration of the cognition-motivation and cognition-control views to assess learner adoption intentions for Web-based learning. Three critical variables affecting learner perceptual processes in Web-based learning are identified: self-efficacy, personal outcome expectations and perceived behavioral control. The model is validated with the support of a (non-adaptive) Web-based learning system.	Self-efficacy is a positive determinant of personal outcome expectations and perceived behavioral control. Personal outcome expectations and perceived behavioral control significantly and positively affect adoption intention and individual attitudes towards WBL. Attitude was found to significantly and positively influence the behavioral intention.	expectations, meta-cognitive abilities
PREFERENCES				
(Acampora, Gaeta, & Loia, 2010) / IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE / 19	Exploring e-Learning Knowledge Through Ontological Memetic Agents	The paper proposes a multi-agent e-Learning system that uses ontologies for knowledge representation and memetic agents for enabling adaptation to learners' preferences.	The flexibility, efficiency and interoperability of the proposed approach are tested empirically.	preferences
(Salehi & Kamalabadi, 2013) / KNOWLEDGE-BASED SYSTEMS / 2	Hybrid recommendation approach for learning material based on ...	A new approach is introduced in order to improve the quality of personalized recommendations. The proposed approach takes into account the order and sequential patterns of the learner's accessed material and rating of learners.	Conducted experiments show that the proposed approach outperforms the previous algorithms in terms of precision, recall, and intra-list similarity measure.	preferences (for particular learning material)

[a] The paper reports null-evidence of variable impact.

enrollment of particular variable in existing systems. Comparison of this study with the work of Chrysafiadi and Virvou (2013) reveals two significant differences. First, the survey of Chrysafiadi and Virvou brings an extensive list of existing systems along with student model characteristics and corresponding approaches to student modeling. On the other hand, the intention of this review is not to present a complete list of existing adaptive systems but to use an exemplary extract of prevailing systems in order to identify the most common sources of adaptation and the tendencies of their further employment in learning systems. The second difference between these two reviews is in the set of targeting student characteristics. The study of Chrysafiadi and Virvou reviews existing systems according to several individual characteristics (knowledge, affective features, motivation, and metacognition) along with certain groupings of similar characteristics into broad categories (learning styles and preferences being one category and cognitive aspects the other), while our review considers student model as a fine graded collection of assumptions about individual student characteristics. For example, cognitive features are decomposed in cognitive styles and a number of cognitive abilities which are explored individually. According to the obtained results, adaptation to working memory capacity could significantly improve learning performance. Furthermore, spatial ability, processing speed, and reasoning ability may be worth modeling, while the effects of adaptation to verbal ability and perceptual speed probably would not justify the related cost and effort. Consequently, considering identified similarities and differences between this review and the one of Chrysafiadi and Virvou, it can be concluded that the studies are complementary in regards to method, obtained results, and mode of their presentation and interpretation. In addition, the research presented in this article is comparable to the work of Vandewaetere et al. (2011), especially in regards to the sound and rigorous methodology for selection of relevant publications. However, the selection of only those publications that bring explicit evidence on adaptation efficiency makes our study distinctive from all presented related works. At the same time, the applied method enables the quantitative representation of employment of each variable as a user model attribute, thus revealing its true contribution to adaptation of learning systems. The timelines of published items and citations in Web of Science Core Collection (Figure 3 and Figure 4) present the state-of-the-art of individual differences in adaptive education. Moreover, the timelines indicate the growth of interest in modeling many student individual characteristics and reveal the tendencies of changes in the structure of student models.

The findings of the study are the most likely affected by restricted access to a number of included publications, which is a severe limitation of the study. In the step 4 of the conducted search procedure, 180 different titles were selected for reading, but the full-texts for only 51 publications were available. Those 51 papers were inspected and 43 of them were accepted for the review, which makes 70% of all available full text publications. For the rest of 139 titles only abstracts were considered and 55 (i.e., 40% of respective papers) were accepted inthe review.

Comparing the acceptance rates of publications on the basis of abstracts and full-texts considerations, it can be assumed that more publications would be accepted if their full-texts were available. Namely, only the abstracts with clear statements about conducted evaluation were considered. The majority of obtained full-text articles and book chapters are available in open access, several publications were reached via institutional login, a number of papers are found in private inventories of the authors of this study, and several papers were obtained in personal correspondence with the authors of those papers. More publications included in open access would significantly contribute to this and other review studies.

Due to the fact that only evaluated systems are considered in this study, a couple of issues on evaluation of adaptive systems has to be discussed: first, the frequency of evaluation studies included in the original papers on developed learning systems, and second, the methodology applied for evaluation of adaptive systems. Considering the ratio of evaluation studies in scientific publications, the progress in the last decade is evident. For example, in *User Modeling and User-Adapted Interaction* (UMUAI) journal, Chin (2001) reported that only one fourth of published papers for the 9 years preceding 2001 involved evaluations of proposed frameworks or developed systems. Continuous emphasis of the importance of conducting and reporting evaluation studies with real users (Gena & Weibelzahl, 2007; van Velsen, van der Geest, Klaassen & Steehouder, 2008; Weibelzahl 2001, 2005) benefited to the extent that at the end of the decade Paramythis, Weibelzahl and Masthoff (2010) reported that all articles, except survey papers and introductions, published in 3 preceding years in UMUAI include evaluation. On the other hand, in their overview related to the sources of adaptation, Vandewaetere et al. (2011) found that only 64.3% of papers bring evaluation studies. This percentage is in line with the review of Akbulut and Cardak (2012) where 65.7% of publications on adaptation to learning styles include evaluations or experiments, while only 62.3% of publications include evaluations with real participants. The growing number of evaluated studies is confirmed by Chrysafiadi and Virvou (2013) who reported that 82.9% of systems included in their survey have been evaluated, mostly by their respective authors. Evaluation of adaptive systems needs to involve end-users and has to be specifically designed to address all aspects of adaptivity (Paramythis et al, 2010; van Velsen et al., 2008). In the last decade, the method of layered evaluation has emerged as a complementary approach to traditional summative and formative evaluation methods and appears to be a more appropriate solution for covering different aspects of adaptive systems development (Paramythis et al., 2010). In addition, research on improvements of criteria to find the valid indicators of interaction quality and adaptivity success is on-going and the new criteria are continuously proposed (Tarpin-Bernard, Marfisi-Schottman, & Habieb-Mammar, 2009; Tobar, 2003). In particular, a number of subjective criteria are acknowledged, such as user perception, motivation, and satisfaction, and usability evaluation methods for appraising these criteria are applied, specifically heuristic evaluation and usability testing (Magoulas, Chen, & Papanikolaou, 2003; Paramythis et al., 2010). The improvement of evaluation methodology is fostered by reports on evaluation studies (van Velsen et al., 2008). A properly documented evaluation study contributes not only to the system development but to the refinement of evaluation methodology as well. This should encourage the authors to publish evaluation studies of the developed adaptive systems even when the null-hypothesis is confirmed.

CONCLUSIONS

The article presents a literature review of user individual differences employed as sources of adaptation in learning systems developed in the 21st century. Twenty-two user individual characteristics were explored in the search procedure and 17 of them were identified as sources of adaptation in the final selection results (age, gender, cognitive abilities such as processing speed, working memory, spatial ability and others, metacognitive abilities, personality, anxiety, emotional and affective states, cognitive styles, learning styles, experience, background knowledge, motivation, expectations, and preferences).

According to the obtained results, the adaptation of learning systems is highly successful when they are adapted to one or more of the following student characteristics: learning styles, background knowledge, cognitive styles, preferences (for particular types of learning materials), and motivation. The tendency of adopting motivation as a criterion for learning success in adaptive education is evident. In general, from 2001 up to the beginning of 2014, the growing interest of researchers is shown for the majority of investigated characteristics. However, results show that after 2001 several characteristics are recognized as particularly important in learning activities, specifically emotions, motivation, and metacognitive abilities. On the other hand, it appears that cognitive abilities and personality are especially attractive characteristics to researchers while the possibilities of adaptation to those characteristics are insufficiently explored.

The review is evidence-based, that is, only evaluated adaptive learning systems are selected and reviewed. This makes the conducted study distinctive from related works and offers insight in learner characteristics which are worth modeling in adaptive systems to provide high learning performance through a pleasant learning experience. Another significant distinction from related studies is the presentation of results in the form of timelines from 2002 to 2014. This quantitative representation of the findings shows current trends in the research of individual differences, as well as the tendencies of their further employment in student modeling.

The article contributes to the body of knowledge on user individual differences and consequently to the research and development of adaptive learning systems. The researchers and developers can recognize the possibilities of adaptation to various user characteristics and appraise what characteristics could serve as the most appropriate sources of adaptation for particular learning environment, thus leading to improvement of user interaction as well as to enhancement of learning performance. Added value of the study is an in-depth description of development and evaluation of the search strategy, which makes the method of the study easily replicable as well as suitable for modification and employment in systematic literature review in any research domain. Further research is needed to establish a firm methodology of adaptive learning systems evaluation, which could effectively address both the pedagogical as well as usability requirements of such systems.

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Corresponding Author:

Dr. Jelena Nakić
Faculty of Science
University of Split
Nikole Tesle 12, 2100 Split
Croatia
e-mail: jelena.nakic@pmfst.hr