Adapting to Student’s Individual Differences: A Step to Better Learning Performance

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Abstract. An e-learning system able to adapt to different learning characteristics of users may improve their performance and increase their learning outcome, as suggested by the research. However, the development of adaptive systems addresses major research questions, identifying and appraising relevant user characteristics as the starting point. Conducted empirical study reveals statistically significant correlations of user intelligence, experience and motivation with her/his learning outcome in an e-learning environment. This contribution adds usefully to the body of knowledge on individual differences and will be considered in an estimation of possible benefits from system adaptive behavior.

Keywords. adaptive systems, e-learning, individual differences, empirical study

1. Introduction

Focusing on e-learning systems it is an accepted attitude that the progress in the field has been slow, associating related problems mostly with poor design of e-learning applications. To improve the learning experience and increase systems’ intelligent behavior, related interaction mechanisms merit additional consideration since in e-learning we do not need interfaces that support "doing tasks", but interfaces that support "learning while doing tasks", cf. [18].

The HCI research has already confirmed and empirically proved that system intelligent behavior strongly relies on individual differences [7; 23] and, on the other hand, has implications on the degree of success or failure experienced by users. Such assumption is in line with related studies completed by the authors; for example [15; 16]. However, developing intelligent systems is the process that includes comprehensive research, in relation to application domain of particular system. Designing intelligent interaction needs to take into account several research questions, including (i) how to identify relevant user characteristics (ii) how to model the user, (iii) what parts of the intelligent/adaptive system shall change and in what way and (iv) how to employ user model to implement adaptivity, cf. [5; 26]. This paper reports on an empirical study considering the first question in a context of education. Particularly, the study identifies and appraises user individual differences and their relevance in learning environment. The identified characteristics are candidate variables for steering the adaptation process towards them.

The paper is structured as follows. Section on adaptive systems outlines basic principles of adaptive systems design and development. Subsequent section provides an overview of individual differences literature in the HCI field in general and e-learning area in particular. Literature findings are discussed in regards to objectives and motivation for current research. Afterward, the empirical study on individual differences is briefly presented. Last section offers discussion and concludes the paper.

2. Adaptive systems

The frequently cited indication of intelligence is the ability to adapt [24], which implies the ability to adjust the interaction outcome to the level of understanding and the interests of individual users. Within the area of system adaptation, a distinction is being made between adaptive and adaptable systems [30]. Adaptable systems allow the user to control the interface customization, while adaptive systems monitor user's interaction and automatically make adjustments based on the system's assumptions about user needs. Adaptive systems dynamically collect information about user (such as her/his goals, skills, preferences and knowledge), store these assumptions in form of user model [7; 24] and then use these assumptions for real-time adjustment of system appearance and behavior to each particular user. Personalizing the system
output encompasses identification of system's adjustable parts, meaning the parts that will look differently or act differently for different users. Subsequently, implementation of adaptivity mechanisms onto adjustable parts of the system is the final step of adaptivity process.

In present adaptive hypermedia systems (AHSs), as defined by Brusilowsky (2001), there are typically two adaptivity mechanisms employed (ibid.):

- adaptive presentation or content adaptation, providing different content of the page for each individual user respecting her/his user model, and
- adaptive navigation support, concerning adaptation of links to other pages, including direct guidance, adaptive link annotation, link hiding (removing and/or disabling) and link sorting as the most commonly used adaptivity techniques.

Table 1 presents several AHSs which employ diverse adaptive presentation and adaptive navigation support techniques: AHA! [10], InterBook2 [6], ELM-ART3 [36], INSPIRE [27] and KBS Hyperbook [17].

Table 1. Adaptation technology in AHSs

<table>
<thead>
<tr>
<th>Adaptation technology</th>
<th>AHA!</th>
<th>InterBook</th>
<th>ELM-ART</th>
<th>INSPIRE</th>
<th>KBS Hyperbook</th>
</tr>
</thead>
<tbody>
<tr>
<td>Content adaptation</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct guidance</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Link annotation</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td></td>
</tr>
<tr>
<td>Link hiding (removing, disabling)</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Link sorting</td>
<td>x</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Designing adaptive systems for educational purpose addresses additional user individual differences, the ones specific for knowledge acquisition process. In their consideration of learning style characteristics, Papanikolaou and Grigoriadou (2004) argue that the development of adaptive educational systems should meet several outstanding research challenges: (i) which models of user individual differences can be used to model learning characteristics, (ii) what are the relevant behavioral features that are indicative of learning characteristics, (ii) how can learners be supported through different kinds of adaptivity and (iv) how can intelligent techniques be developed and employed to diagnose learning preferences and to dynamically adapt the system.

In order to meet the first research challenge, a literature review on user individual differences in the HCI field follows as an attempt of their theoretical appraisal. Special consideration is given to the characteristics employed in user models of adaptive educational systems. In order to empirically evaluate the relevance of several user characteristics proposed in literature, we have conducted the experimental research briefly presented subsequently to the literature review.

3. Individual differences

In the initial comprehensive overview of individual differences in the HCI field, Egan (1988) suggested that user differences could be understood and predicted as well as being modified through the system design. In their early consideration of adaptivity, Browne, Norman and Riches (1990) provided one of the first classifications of candidate dimensions of user differences that may impact computer usage. They included diversities in cognitive styles, personality factors, psycho-motor skills, experience, goals and requirements, expectations, preferences, cognitive strategies and a number of cognitive abilities. Dillon and Watson (1996) summarized that measures of ability can account for approximately 25% of variance in performance thus being suitable for usage in decision making for most systems. According to their suggestions, psychological measures of individual differences should be used to increase possibilities for generalization of HCI findings. There is a number of studies confirming these pioneer work suggestions, for example showing that cognitive abilities such as spatial and verbal ability do affect the interaction, particularly navigation performance of the user [2; 21].

The influence of user goals, knowledge, preferences and experience on her/his interaction with an intelligent system is unquestionable [5]. Moreover, these characteristics have been successfullly employed in many adaptive systems, such as KBS Hyperbook [17], ELM-ART [36], AVANTI [33] and PALIO [34].
On the other hand, the matter of adaptation to cognitive styles and learning styles has been mainly ignored until last decade. Nevertheless, newer research (e.g. [8; 14]) confirm that navigation preferences of users reflect their cognitive styles in several dimensions: field dependent vs. independent, as defined by Witkin, Moore, Gooddenough and Cox (1977), holist vs. serialist [28], verbalizer vs. imaginer [29]. In related study, Chen and MacRedie (2002) found that field dependent learners prefer guided navigation, while field independent favor navigation freedom. Graff (2005) also showed that individuals identified as having verbaliser and imager cognitive styles apply different browsing strategies.

In educational area many authors have concluded that adaptation to learning styles, as defined by Kolb (1984) or Honey and Mumford (1992), could bring substantial benefits to students’ learning activities. This is evident from an increasing number of adaptive educational systems having implemented some kind of adaptation (adaptability or adaptivity) to learning styles, see for instance INSPIRE [27] or AHA [31].

Evidently, the effect of user individual differences on her/his performance has been the topic of 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. Besides, the research area of cognitive styles and learning styles in HCI is very recent so yet there is no strong evidence about their relevance regarding user’s interaction with an intelligent system (as discussed in [32]). In addition, 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 improving user’s performance [18]. Moreover, it can be disadvantageous to some classes of users [9]. Before including adaptation into a system, it is worthwhile considering possible alternatives. A good option, suggested by Benyon and Hook (1997), could be increasing learner’s experience in order to overcome her/his low spatial ability. The second alternative is an appropriate redesign of a non-adaptive interface [20].

Based on these reflections, the research presented in this paper encompasses a comprehensive user analysis regarding a web-based learning application. The empirical study concisely reported in the following aims to provide an answer whether it is reasonable or not to implement adaptation into the system.

4. An empirical study on individual differences in e-learning environment

The objective of the experiment is to identify and appraise those users' characteristics that produce statistically significant differences in the "amount of knowledge" which students get in a learning session (i.e. learning outcomes).

4.1. Procedure

Participants were recruited among undergraduate and graduate student volunteers from two faculties of the University of Split [25]. User individual differences concerned as predictor variables include: age, personality factors, cognitive abilities, experience, background, motivation and expectations from e-learning.

General factor of intelligence or "g" factor, as defined by Sternberg (2003), was assessed through M-series tests as a single cognitive ability measure. The Eysenck’s Personality Questionnaire (EPQ) was used to measure students’ personality factors: extraversion vs. introversion and the level of neuroticism [13]. We have used a Likert-based questionnaire to measure students’ experience, motivation and expectations. There were three dimension of experience assessed: computer experience and Internet experience which refer to time students spend using computer and Internet at the present time (Internet experience thus being a subset of computer experience), as opposed to prior experience in using computers that refers to their previous education. Motivation for e-learning was the most difficult variable to measure, intending to reach students’ intrinsic motivation, namely aspiration and effort to achieve a learning goal. Students’ expectations from e-learning are another subjective measure, estimated through their own opinion about the quality and efficiency of e-learning applications in general. Information about students’ background, i.e. previous knowledge was calculated on their grades from previously passed exams and/or pre-exams. Prior experience and background knowledge are partially related. Still they are considered as two different variables, since different sources for their assessment ensure they do not completely overlap.
A lesson on communication and collaboration of Internet users was selected as learning material, provided through a learning management system. The lesson has not been thought previously in any university course at both faculties. Students’ outcome acquired in learning session is expressed as a gain between pre-test and post-test scores. Finally, the students were asked to fill the SUS questionnaire [3] measuring their satisfaction with the system they have just experienced.

4.2. Results

A total of 33 datasets were analyzed using SPSS version 16.0 for Windows. The sample consisted of 12 females (36.4%) and 21 males (63.6%). The age varied from 18 to 24, with a mean of 20.3 [25]. Pearson correlations were calculated, with p < 0.05 as acceptable level of significance for the experiment. Correlations of all predictor variables with learning outcome and satisfaction with the system usage are presented in Table 2.

Table 2. Pearson correlations of user individual differences with her/his learning outcome and satisfaction

<table>
<thead>
<tr>
<th>User individual differences</th>
<th>Learning outcome</th>
<th>Satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>.333</td>
<td>.276</td>
</tr>
<tr>
<td>Extraversion</td>
<td>-.088</td>
<td>.043</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>.184</td>
<td>.260</td>
</tr>
<tr>
<td>Intelligence</td>
<td>.465**</td>
<td>.035</td>
</tr>
<tr>
<td>Prior experience</td>
<td>.284</td>
<td>.139</td>
</tr>
<tr>
<td>Computer experience</td>
<td>.180</td>
<td>.116</td>
</tr>
<tr>
<td>Internet experience</td>
<td>.370*</td>
<td>.094</td>
</tr>
<tr>
<td>Motivation</td>
<td>.357*</td>
<td>.184</td>
</tr>
<tr>
<td>Expectation</td>
<td>-.026</td>
<td>.346*</td>
</tr>
<tr>
<td>Background knowledge</td>
<td>.314</td>
<td>.205</td>
</tr>
</tbody>
</table>

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Data analysis related to user individual traits showed highly significant correlation of intelligence and learning outcome (r = 0.47, p < 0.01). This result suggests that more intelligent students (in terms of "g" factor as one of the many classifications of intelligence [35]) have learned more in the e-learning session. The probability of occurring this by chance is less then 0.01. This correlation is consistent with connection obtained between intelligence and background knowledge (r = 0.39, p < 0.05), indicating that more intelligent students have also achieved better grades on their previously passed exams and/or pre-exams, as expected. No significant correlations were found between personality factors and learning outcome.

Conducting age and experience analysis we have found that Internet experience significantly correlates with learning outcome (r = 0.37, p < 0.05). Apparently, students who spend more time on the Internet use web-based learning application more successfully.

Intrinsic motivation for e-learning positively correlates with learning outcome (r = 0.36, p < 0.05), suggesting that more motivated students have acquired more knowledge in learning session. Another statistically significant correlation (r = 0.35, p < 0.05) was found between expectations from e-learning and satisfaction in using the system. It seems that users with greater expectations from the system have experienced higher levels of fulfillment in system usage.

5. Discussion and conclusion

Adaptive systems are designed to adjust their presentation and functionality to individual needs, wishes and abilities of the user. Still, they significantly differ in regards to: what individual characteristics of the user they take into account in order to tailor adaptation, how they observe user’s actions and gather that information and finally how they employ these characteristics to perform adaptation. The richness of human behavior and technological opportunities emerges even greater diversities in applied technology. Nevertheless, adaptive systems commonly rely on user model as an explicit way of representing and updating user characteristics, preferences and behavioral patterns.

Appraising learner’s characteristics that produce differences in learning performance has a crucial role when considering user modeling in adaptive educational systems. The conducted empirical study reveals statistically significant correlations of user intelligence, experience and motivation with her/his learning outcome in an e-learning environment. User individual differences in experience level could be increased by training; at the same time learner’s motivation could be actuated by adding external stimulus for learning, like course grades. On the
other hand, general factor of intelligence, as relatively stable user variable [35], could hardly be influenced. The possibility for overcoming students’ differences in intelligence, like in all other cognitive abilities, is by increasing their experience (cf. [2]), on contrary to the possibility of meeting these differences through system adaptation. An intention to build adaptive system that appropriately adjusts to students with lower cognitive abilities poses additional research challenges – are there any significant differences in students’ learning behavior related to the level of their cognitive abilities. In such case the system adaptation should be enabled in order to dynamically diagnose user’s navigational pattern, as suggested in [5; 26], and to provide such navigation support that allows the user to browse through instructional content in individualized navigational path thus leading her/him to the best learning achievement possible. Subsequently, the benefits of such adaptive behavior should be evaluated in terms of efficiency and effectiveness as well.

Data analysis concerning background knowledge as a predictor candidate of learning outcome showed no statistically significant correlation. This correlation was anticipated accordingly to related studies e.g. [5], including the pilot study previously completed by the authors, see [16]. The absence of particular connection may be explained by the fact that the topic of learning session was previously unknown to majority of participants, as confirmed by the pre-test scores.

It seems that personality factors, namely extroversion vs. introversion and the level of neuroticism have no impact on learning outcome, the results which are in line with related literature [11, 12].

These empirically obtained results contribute to the body of knowledge on user individual differences and they should be taken into account when developing a web-based instructional content. It can be assumed that adaptation of the system to those user characteristics that significantly correlate with learning outcomes could bring substantial benefits to students’ learning performance. Such hypothesis still has to be confirmed or rejected experimentally for each one of the candidate variables.

Further work is required in order to determine the way in which relevant user characteristics could be exploited in order to enable the system adaptation. Additional research will be conducted to investigate what affects learning behavior as well as to determine how learning behavior is reflected on learning outcomes. It will be particularly interesting to see if the predictors of the learning behavior could predict learning outcome as well.

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7. References


