Designing Intelligent Interfaces for e-Learning Systems: The Role of User Individual Characteristics

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Abstract. In order to advance personal learning experience it is crucial to overcome the one-size-fits-all approach in user interface design and increase the e-learning systems intelligent behavior. Recent research has confirmed that user individual characteristics must be taken into account to accomplish that goal. This paper identifies user features relevant for system's adaptation in general. Aiming to investigate affect of those features on users' learning outcomes in e-learning environment in particular, an empirical study along with obtained results is reported as well.

Keywords: intelligent user interfaces, adaptive user interface, e-learning, individual differences.

1 Introduction

"We have spent the last 50 years learning how to create computers and how to program computers. The next frontier is in actually making computers serve and adapt to human needs rather than forcing humans to adapt." claimed Dan Olsen in the already remote ACM UIST 97 panel on the future of human-computer interaction (HCI) [13, p. 118]. In order to achieve a better fit to this agenda, recent HCI research with its user-centered design [18] and learner-centered design [24] approaches puts the user, the individual at the centre of all developments, stressing the importance to design technologies for human needs. Consequently, the role of an intuitive user interface and a flexible interaction suited to different needs becomes even more important for the users' success, as users with a wide variety of background, skills, interests, expertise and goals are using computers for quite diverse purposes. In such context, the role of intelligent user interfaces (IUI) is unquestionable. IUIs should facilitate a more natural interaction between users and computers, not attempting to imitate human-human communication, but instead aiding the human-computer interaction process [12]. User modeling, as one of the employed techniques in IUI area, is used to denote a model of the user that the system maintains and adapts its behavior to. As the range and complexity of interactive system increases, understanding how a system can dynamically capture relevant user needs and features, and subsequently adapt its interaction, has become vital for designing effective interfaces.

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Focusing on e-learning, an instructional content or learning experience delivered or enabled by electronic technology [19], despite so much publicity and activity, the progress in the field has been unexpectedly slow. In order to improve the learning experience and increase e-learning system's intelligent behavior, respective interaction mechanisms merit additional consideration. Apparently, there should be a synergy between the learning process and a user's/learner's interaction with the e-learning application [25], additionally taking into account the different ways user's learn and ensuring their natural and flexible interactions as well. Most of the current e-learning applications are static and inflexible, designed without considering users' preferences and abilities. It is vital to overcome the one-size-fits-all approach and provide users with individual learning experiences through e-learning systems with intelligent user interface.

Our research has been focused on the employment of intelligence in e-learning system's interface with the intention of adjusting the system to individual users. In order to design adaptive interaction in e-learning applications, our recent work includes an application of adaptation techniques, along with methodology of user modeling, from the field of adaptive hypermedia (AH) [9]. To enhance and to broaden this AH based approach, we have analyzed user features revealing personal differences relevant for system intelligent behavior in the HCI field in general, as well as identified and quantified those we find significant for e-learning system adaptation in particular. In this paper we concisely inform about those features in both domains and then report the role of individual user characteristics in design of intelligent user interfaces for e-learning systems. The main objective of the presented research study was to examine the affect of users' individual differences on their learning outcomes achieved in e-learning environment. Obtained results will enable a more precise design of adaptation technology in e-learning systems.

The rest of the paper is structured as follows. Section 2 brigs taxonomy of user features revealing individual differences and stresses the importance of intelligent systems to adapt individual users, especially in educational environment. The empirical study presented and discussed in Section 3 aimed to investigate the role of users' personal characteristics in their knowledge acquisition process while using e-leaning application. Section 4 summarizes achieved results and concludes the paper.

2 Background

IUIs have been recommended as a means for making systems individualized or personalized, thus enhancing the systems flexibility and attractiveness [12]. The intelligence in interface can for example make the system adapt to the needs of different users, take initiative and make suggestions to the user, learn new concepts and techniques or provide explanation of its actions *cf.* [12], [15].

The research in HCI field has already confirmed and empirically proved that system intelligent behavior strongly relies on individual differences [6], [7], [8], [14], [16], and on the other hand has implications on the degree of success or failure experienced by users. When considering adaptation of system to individual use, user personality and cognitive factors have to be taken into account because of their higher resistance to change. Moreover, it is useful to exploit a certain amount of "stable" knowledge about the user conveyed through long-term characteristics, containing information about user's level of expertise with computers in general, her/his expertise with the system in particular, as well as familiarity with the system's underlying task domain. Certain information related to user's preferences or current goals conveyed through short-term user characteristics should also be taken into account. Table 1 provides taxonomy of key user characteristics for system adjustment and brings in several authors who consider them important for user description as well. Those features are generally categorized as:

- *personal user characteristics*, quite stable over time and independent from the system, where (i) general personal characteristics (including characteristics that reflect internal psychological state) and (ii) previously acquired knowledge and abilities can be differentiated, as well as
- *system-dependent user characteristics*; the most changeable category of characteristics as related to particular system.

Table 1. User characteristics revealing individual differences; A-Benyon and Murray [2], B-Egan [7], C-Browne *et al.* [3], D-Norico and Stanley [17], E-Dillon and Watson [6], F-Rothrock *et al.* [23]

		A	*B*	*C*	*D*	*E*	*F*
personal characteristics	gender	●	●			●	●
	age		●			●	
	personality & affections	●	●	●		●	●
previously acquired knowledge and abilities	experience	●	●	●	●	●	●
	cognitive abilities	●			●	●	●
	psycho-motor skills			●		●	●
	technical aptitudes		●		●		
	domain knowledge	●	●	●	●	●	●
system dependent characteristics	goals & requirements			●		●	●
	motivation			●		●	●
	expectations			●			●

Yet, when considering e-learning systems, it has been claimed that "… although technology is often touted as the great salvation of education – an easy way to customize learning to individual needs – it rarely lives up to this broad expectation" [11, p. 398]. Interest received by user modeling aspect has not succeeded to address the variety and richness of the educational environment, even in the terms of user individual characteristics. Learners have different requirements like their individual learning style, their actual learning in the learning process and their individual background knowledge. These issues have been ignored for quite a long, hoping that new technology will somehow resolve the lack of real progress. The experience has proved so far that these issues cannot be wished away as they determine the type and scope of e-learning systems that are likely to succeed [20].

3 Research Method

The experimental study reported in the following aimed to question existence and level of interaction between users' individual differences and learning outcomes achieved while using an e-learning application. Personal user features assumed to affect learning process were clearly identified and the methods how to measure them were determined. We have classified characteristics intended to be measured in two categories: (i) intelligence and personality factors, and (ii) experience, motivation, expectations and background knowledge.

3.1 Subjects

Undergraduate students of the fourth semester from two different university programs (mathematics–computer science and physics–computer science) were recruited to the briefing where they have been introduced with nature and purpose of the experiment. Since we intended to use an e-learning application on programming domain in this study, we have consequently selected twenty-four students (6 males and 18 females) among volunteers who hadn't taken an exam on Programming I before. The participants of the study have been told that their achievement on test would have only experimental use and would not affect their future exam grades.

3.2 Research Instruments

Standard psychological tests were used to measure subjects' personal characteristics. Intelligence test (D-48) measured general mental abilities, while personality test (EPQ) measured dimension of emotional stability/instability, extraversion/introversion, mental stability/psychoticism and honesty/dissimulation level [21]. Those tests are protected by national laws and regulations so cannot be presented here.

A questionnaire was developed in order to obtain students' gender, experience in using computers and Internet, motivation and expectations from e-learning. Students' grades from Introduction to Computer Science exam were taken as a measure of their background knowledge to material supposed to be learned during the experimental session.

E-learning application used to test students' knowledge is an intelligent tutoring system developed and evaluated on our faculty [26]. Intelligent tutoring systems (ITSs) are computer-based educational systems which emulate human teacher in order to support the process of learning and teaching in arbitrary domain knowledge [4]. We consider this Web-based application as well-accepted instrument for this research since its effectiveness has been evaluated in several case studies, e.g. [10], and it has been shown that system can support at least 20 users at a time.

Participants of the experiment were already familiar with functionality of the ITS since similar systems (generated from the same authoring shell [26]) have been used in university courses in the first and second semester. However, the students have never had access to learning modules or quiz related to course Programming I, which were selected to facilitate in this study.

3.3 Procedure

Experiment was conducted through five steps as shown in Fig. 1. First, a physiologist and a HCI professor interviewed the experimental group of students in order to introspect some general characteristics of the group so they could design a questionnaire related to their experience in using computers and Internet, motivation and expectations from e-learning and concrete system. Few days after the introductory interview the participants were invited to take intelligence test and personality test.

Two experimental sessions in an on-line classroom were conducted for groups of 12 students at a time. Students were not allowed to take notes or use any external learning material, paper or on-line, besides the system lessons on selected ITS. They were free to learn for 30 minutes, and then began to test acquired knowledge on a quiz belonging to particular ITS simultaneously. Time for testing was limited to 15 minutes and all participants completed the quiz at given time.

After completing the quiz, students were asked to fill in the multiple choice questionnaire prepared to gain data about their gender, prior experience in using computer and Internet, motivation to learn programming, expectations from e-learning systems in general and also expectations and satisfaction with an ITS they have just exploited.

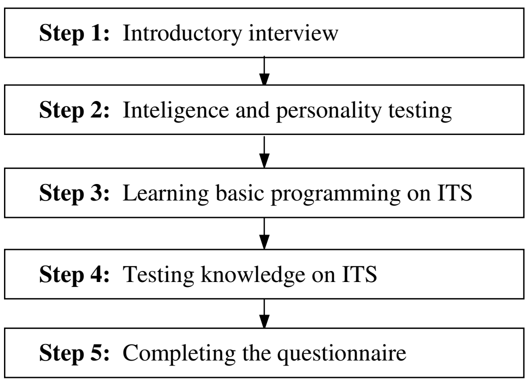

Fig. 1. Five-steps procedure of the experiment

3.4 Results

Data analysis of 24 complete datasets was performed using Statistica 7 software package. All variables (except gender) were measured on interval scales and relations between variables are expressed by Pearson correlations [22]. Significance level of $p < 0.05$ was considered acceptable for this research. We ensured that obtained values of all relevant variables were normally distributed (e.g. quiz results have Chi-Square test = 1.16499, df = 1 (adjusted), p = 0.28043). Since 24 participants constitute a small sample, the sample has been analyzed as a whole, without splitting at the mean by any variable.

Although the main issue of the research was to investigate the influence of user individual differences on their learning outcomes accomplished on e-learning system, it was inspiring for us to see if there were any connections among individual differences of the users themselves. Some interesting correlations were found between intelligence and personality factors obtained by tests with other user characteristics obtained by questionnaire. Those results are given in Table 2. Significant correlations were found between mental stability and motivation ($r = -0.50$, $p < 0.05$) and also between emotional stability and expectations from using the system ($r = -0.45$, $p < 0.05$). This means that mentally stable students are more motivated to learn programming then mentally unstable or "more neurotic" students. Similar to that, emotionally stable students have greater expectations from e-learning than emotionally unstable or "more psychotic" students. Highly significant correlation was found between students' prior experience in using computers and Internet and their background knowledge required to learn programming ($r = 0.62$, $p < 0.01$) as expected. It seems that students' intelligence and dimension of extraversion/introversion are not associated with any other individual characteristics.

Table 2. Pearson correlations between user individual characteristics

	Intelligence	Emotional stability	Extraversion	Mental stability	Experience
Experience	0.22	-0.28	0.19	-0.18	
Motivation	-0.17	-0.08	0.07	-0.50*	0.16
Expectations	-0.11	-0.45*	0.36	-0.26	0.01
Background	0.39	-0.28	0.06	-0.11	0.62**

*Significant correlations at level of $p < 0.05$.
** Significant correlations at level of $p < 0.01$.

Table 3 shows correlations between students' individual differences and their learning outcomes accomplished while using e-learning application. Apparently there are no associations between intelligence and personality factors with learning outcomes. Considering characteristics obtained by questionnaire, it seems that only motivation to learn programming in addition to expectations of e-learning has

Table 3. Pearson correlations between user individual characteristics and knowledge acquired on e-learning system

	Intelligence	Emotional stability	Extraversion	Mental stability	Experience
Knowledge	0.05	-0.29	-0.00	-0.15	0.29

	Motivation and expectations	Background
Knowledge	0.42*	0.26

* Significant correlations at level of $p < 0.05$.

statistically significant impact on knowledge acquired through interaction with the system ($r = 0.42$, $p < 0.05$).

Analysis by age and by prior experience in using concrete system was not conducted because individual differences among participants were minor in those variables. Also, analysis by gender would be ineffectual because the subjects group consisted of 6 males and 18 females, which are small samples.

3.5 Discussion

There are numerous studies reporting minor influence of personality factors on predictions of user performance (reviewed in [6]) or no influence at all [7], so the perceived lack of associations between intelligence and personality with learning outcomes in our analysis was not quite unexpected.

However, careful interpretation and observation of the obtained results revealed some shortcomings of applied methodology. First of all, the sample we analyzed was too small and too homogenous to give us strong grounds for generalization of the results. All participants of the experiment were students of the same age, with comparable background knowledge and experiences, intellectual capabilities and motivation for graduating as well. Similar experiment with larger sample of more diverse users would certainly provide more reliable results. Thus we consider this study as a pilot experiment that gave us important directions to establish an enhanced methodology for future research.

When we observe the connection between subjects' experience in using computers and Internet with their background knowledge related to programming (see Table 2), the lack of similar connection with their quiz scores ($r= 0.26$ as shown in Table 3) was quite unexpected. This result is more surprising in comparison to related work firmly confirming the major affect of experience on task outcomes e.g. [5], [7], [8], [17]. Part of the explanation of that result could be found in insufficient diversity of students' experience. Besides that, we cannot ignore a procedural issue that possibly caused more homogenous scale of quiz results then expected. The ITS on programming domain was selected for the research because none of the subjects hadn't taken an exam on Programming I before participating in experiment and knowledge tested on the ITS was accepted as reliable variable for the experiment [10]. Still, many of the students participated in experiment had attended classes related to programming which could have increased their background knowledge on particular domain. One possible solution of that situation is to select an ITS on some other domain knowledge, completely unknown to the subjects. Even better solution is to give them a pre-test and post-test (best the same as pre-test) from the same domain knowledge we intended to measure. This could be paper-and-pen test or simply the quiz on particular ITS, given before and after the learning session. The gain between those two tests scores would be considered as learning outcome achieved on e-learning system only through that particular session. In addition, the time required to complete the test could be used as another aspect of learning outcome for each participant (as suggested e.g. in [1], [7]).

Since a number of participants achieved relatively high dissimulation level on personality test it is possible that they have unrealistically high opinion on their own knowledge. According to that assumption we computed correlation between students' answers on two questions measuring their expectations of e-learning (see Table 4) but found no actual connection between those answers. This result is in contrary to empiric hypothesis that students who consider e-learning effective would be satisfied with their learning outcomes. Possible explanation is that a question positioned between those two and regarding their grades achieved on quiz, affected their answers on following question. Although we cannot affect the subjects' honesty/dissimulation level, more careful composing and reliability analysis of requisite questionnaire, as well as increasing number of questions regarding particular variable would obviously lead to more accurate measurements of user characteristics.

Table 4. Correlation between two questions regarding users' expectations of e-learning

Question no. 7.	You consider e-learning generally a) very efficient and necessary nowadays b) efficient but not necessary c) medially efficient d) inefficient e) inefficient and distressing
Question no. 9.	You think your grade on the quiz is a) completely accurate measure of knowledge b) very accurate measure of knowledge c) half-accurate measure of knowledge d) barely measure of knowledge e) no measure of knowledge at all
r = 0.39	

In this study we did not investigate the affect of experience in using concrete e-learning application on learning outcomes on the same application. This could be done by comparing the learning outcomes of two independent groups of subjects, one experienced in using similar ITSs (generated from the same authoring shell but for different domain) and the other without such experience.

4 Conclusion

Intelligent user interfaces should facilitate a more natural communication between users and computers, aiding the human-computer interaction process. Our research has been focused on the employment of intelligence in e-learning system's interface in order to adjust the system to individual users. In account to that we have analyzed and reported user features revealing personal differences relevant for system intelligent behavior in the HCI field in general, and in educational domain in particular.

This paper also presents the empirical study we have conducted in order to examine the influence of users' individual differences on their knowledge acquisition process in e-leaning environment. We have analyzed interrelations among quantified personal characteristics and found positive associations of mental stability with motivation and emotional stability with expectations from e-learning. Highly significant correlation was discovered between students' prior experience in using computers and Internet with their background knowledge, but similar connection of experience and learning outcomes achieved on the e-learning application was not found. This experiment indicated that motivation to learn programming in addition to expectations of e-learning significantly affects on users' learning achievement.

The observed sample had certain limitations, especially considering the number and diversity of subjects who were all students of the same age. Aware of the great sensitivity of results to the sample, instead of generalization of presented results we have used them to determine the guidelines for developing further research design. Such research is clearly needed to be conducted in order to provide us stronger foundations for designing adaptation mechanism of e-learning systems.

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