User Individual Differences in Intelligent Interaction: Do They Matter?

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Abstract. Designing an intelligent system, as confirmed by research, must address relevant individual characteristics of users. This paper offers a brief review of individual differences literature in the HCI field in general and e-learning area in particular. Research suggests that using adaptive e-learning systems may improve user learning performance and increase her/his learning outcome. An empirical study presented in this paper encompasses a comprehensive user analysis regarding a web-based learning application. Statistically significant correlations were found between user intelligence, experience and motivation for e-learning with her/his learning outcome accomplished in an e-learning session. These results contribute to the knowledge base of user individual differences and will be considered in an estimation of possible benefits from enabling the system adaptivity.

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

1 Introduction

System intelligent/adaptive behavior strongly relies on user individual differences, the claim which is already confirmed and empirically proved by Human-Computer Interaction (HCI) research [6, 12, 13, 15, 22, 25]. Such assumption is in line with related studies completed by the authors; for example [17, 18]. However, developing adaptive 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 adaptive system shall change and in what way and (iv) how to employ user model to implement adaptivity [4]. This paper describes an empirical study considering the first question in context of education. Particularly, the study identifies and appraises user individual differences and their relevance in learning environment.

The paper is structured as follows. An introductory section provides a brief review of individual differences literature in the HCI field in general and e-learning area in particular. Literature findings are discussed in context of objectives and motivation for the research. Subsequently, the exploratory study is presented, along with results and discussion. Finally, conclusions are drawn and future research work is identified.

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1.1 Individual Differences in HCI: A Literature Review and Discussion

The first step in enabling a system to adapt to individual use is identifying and acquiring relevant information about users. The initial comprehensive overview of individual differences in the HCI field is Egan's (1988) report on diversities between users in completing common computing tasks such as programming, text editing and information search. He pointed out that the ambition of adaptivity (e.g. dynamic or real-time adaptation) is that not only "everyone should be computer literate" but also that "computers should be user literate", suggesting that user differences could be understood and predicted as well as being modified through the system design.

Since then, the diffusion of technology brought computers to wide user population with extensive variety of knowledge, experience and skill dimensions in different areas. Accordingly, the identification of individual differences relevant for a system adaptation became a critical issue. 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 (field dependence/independence, impulsivity/reflectivity, operation learning/comprehension learning), personality factors, psycho-motor skills, experience, goals and requirements, expectations, preferences, cognitive strategies and a number of cognitive abilities.

Later on, Dillon and Watson (1996) reviewed a century of individual differences work in psychology stressing the role of differential psychology in the HCI field. They have identified a number of basic cognitive abilities that have reliably influenced the performance of specific tasks in predictable ways. Based on own analyses, they 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, especially in addition to other sources of information (previous work experience, education, domain knowledge, etc.) According to their recommendations, psychological measures of individual differences should be used to increase possibilities for generalization of HCI findings. There is a number of studies confirming these pioneer work suggestions, showing for example that cognitive abilities, such as spatial and verbal ability, do affect the interaction, particularly navigation performance of the user [2, 9, 23, 27, 34].

The influence of user goals, knowledge, preferences and experience on her/his interaction with an intelligent system is unquestionable [4]. Moreover, these characteristics have been successfully employed in many adaptive systems, for example AHA![1] [11], InterBook[2] [5], KBS Hyperbook [19], ELM-ART[3] [33], INSPIRE [26], AVANTI [30], PALIO [31].

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, 16]) confirms that navigation preferences of the users reflect their cognitive styles. In educational area many authors 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

[1] http://aha.win.tue.nl/

[2] http://www.contrib.andrew.cmu.edu/~plb/InterBook.html

[3] http://apsymac33.uni-trier.de:8080/Lisp-Course

educational systems having implemented some kind of adaptation (adaptability or adaptivity) to learning styles, see for example CS388 [7], INSPIRE [26] and AHA [28].

1.2 Motivation for the Research

Evidently, the affect 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 [3]. In addition, the research area of cognitive styles and learning styles in the HCI field is very recent so yet there is no strong evidence of their relevance concerning user's interaction with an intelligent system (as discussed in [29]). Furthermore, even if these user styles were proved to be relevant, the question of potential benefits from personalized interaction still remains. System adaptation, even when well designed, does not necessarily imply user's performance improvement [8]. Moreover, it can be disadvantageous to some classes of users [10]. Before including adaptation into a system, it is worthwhile to consider the possible alternatives. One good alternative, as suggested by Benyon and Hook (1997), could be an enlargement of learner's experience in order to overcome her/his low spatial ability. As a second alternative, an appropriate redesign of a non-adaptive interface can be considered [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 reported in the following aims to provide an answer whether it is reasonable or not to implement adaptation into the system.

2 User Analysis in e-Learning Environment: An Empirical Study

The methodology for this experiment has been grounded mainly on our previous exploratory study reporting the relevance of user individual characteristics on learning achievements acquired in interaction with an e-learning system [18]. Although we have found some statistically significant correlations of user individual characteristics and learning performance, the results were not suitable for generalization, mainly due to certain limitations of the participants sample and of methodology applied.

Encouraged by the results of the pilot experiment but also aware of its limitations, we have redesigned the methodology and conducted the second study elaborated in the following. The main objective of the research remains the same – to estimate potential benefits of engaging adaptation into the system. Clearly, such estimation should be based on in depth user analysis comprising both the analysis of user individual differences and user behavior in e-learning environment.

In particular, the presented empirical study identifies and appraises those users' characteristics that produce statistically significant differences in the "amount of knowledge" which students get in learning session (i.e. learning outcomes). These characteristics are candidate variables for steering the adaptation process towards them. 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.

2.1 Participants

Student volunteers were recruited from two faculties of the University of Split. The first group of participants was selected among 30 first-year undergraduate students (from two different study programs) attending The Computer Lab 1, a laboratory classes at the Faculty of Science. The second group was chosen from 30 candidates of first-year graduate students who were taking the Human-Computer Interaction course at the Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture. Overall, fifty-two students agreed to take part in the study and five of them were engaged to assist in carrying out the procedure. The experiment was completed over four weeks in class. Consequently, there was a number of students who did not accomplish all phases of the procedure, partially because of certain technical limitations occurred at the days of the learning sessions. A total of 33 students completed the study.

2.2 Variables and Measuring Instruments

User individual differences concerned as predictor variables include: age, personality factors, cognitive abilities, experience, background, motivation and expectations from e-learning.

The Eysenck's Personality Questionnaire (EPQ) was used to measure students' personality factors. According to Eysenck (1992) one of the two main personality factors is neuroticism or the tendency to experience negative emotions. The second one is extraversion, as the tendency to enjoy positive events, especially social events. General factor of intelligence or "g" factor, as defined by Sternberg (2003), is a cognitive ability measure assessed through M-series tests, consisting of 5 subtests.

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, 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. Although the learning sessions were integrated in the class, the students' learning performance did not affect their course grades. That was the way to prevent interfering of extrinsic motivation for learning. The motivation assessed through the questionnaire refers only to intrinsic motivation of students, i.e. the level of their interest in the subject matter and in the mode of its presentation as web-based application. 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 (for graduate students) or from entry tests and pre-exams of first-year courses (for undergraduate students) in addition to their high school grades of relevant subjects.

Students' outcome acquired in learning session is expressed as a gain between pre-test and post-test scores. The same paper-based 19-item multiple choice test served as pre-test and post-test. A lesson related to a communication and collaboration of Internet users, provided through a learning management system, was selected as a topic of the learning session. Selected lesson has not been thought previously in any university course at both faculties.

2.3 Procedure

The whole experiment procedure was conduced as a part of usual class time, integrated into the courses curriculums. It took four weeks to carry out all phases of the procedure. Through an introductory interview we have informed the students about the purpose and nature of the experiment. They have been told that participation in the study is on voluntarily basis and that their performance or scores on tests will not affect their course grades in any way. Obtained participants' data were used for the preparation of a finely tuned questionnaire used afterwards to assess their experience, motivation and expectations.

In the second week of the experiment the participants attained M-series tests. Testing was conducted under the supervision of psychologist and took 45 minutes for fulfillment of 5 tests, each one of them time limited separately. A following week the students took the EPQ test and filled the prepared questionnaire which measured remaining personal characteristics.

The last week of the procedure comprised four steps. First, the students were given the pre-test on the subject matter expected to learn afterwards using the e-learning system. They were allowed 10 minutes to complete the pre-test. Then the students started a web-based learning application. Time for learning was limited to 30 minutes. The students were permitted to take notes while reading, but not allowed to use any external material on the subject, such as textbooks or other web resources. These notes could serve them only in reviewing the lesson material. After completing the learning session, the students were given the post-test. Again, a maximum of 10 minutes was allowed for completing the test. Usage of the notes taken while learning was not permitted. On completion of the post-test, the students were asked to fill the SUS questionnaire, thus measuring their satisfaction with the system they have just experienced.

3 Results

Data analysis was conduced using SPSS version 16.0 for Windows. Pearson correlations were calculated, with $p < 0.05$ as acceptable level of significance for the experiment.

3.1 The Sample

A total of 33 datasets were analyzed. 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. The distribution of gender and age is shown in Table 1, distinguished into different study programs of students.

Table 1. The distribution of gender and age within the sample

Study program	Study	Female	Male	Age range	Average age
Computer Science and Technics	undergraduate	2	10	18-21	22.0
Mathematics	undergraduate	8	0	18-20	19.1
Computer Science	graduate	2	11	21-24	19.3
Total		12	21	18-24	20.3

Descriptive statistics of all measured variables is presented in Table 2. The sample is relatively heterogeneous, considerable differences are evident in prior experience as well as background knowledge. This can be explained by the fact that participants come from three different study programs of two faculties. Two groups of participants are composed of first-year undergraduate students, while the third group is recruited from first-year graduate students. Regardless the differences in student experience, neither of participants has previously read any lesson from the learning management system used in the experiment.

Table 2. Descriptive statistics of the sample

	Minimum	Maximum	Mean	Std. Deviation
Age	18	24	20.30	1.72
Extroversion	3	21	14.18	4.43
Neuroticism	1	18	9.48	4.37
Intelligence	36	60	49.15	6.79
Prior experience	6	54	25.64	15.22
Computer experience	4	16	9.64	3.62
Internet experience	4	16	9.52	3.36
Motivation	0	8	6.30	1.81
Expectations	0	6	4.12	1.41
Background knowledge	8	56	27.30	12.34
Learning outcome	10	43	30.52	6.90
Satisfaction	47.5	95	74.545	12.63

3.2 Results and Interpretation

Data analysis showed highly significant correlation of M-series tests results with learning outcome ($r = 0.47$, $p < 0.01$). Since learning outcome is measured as a gain between pre-test and post-test scores, this result suggests that more intelligent students have learned more in the e-learning session then the less intelligent ones. The probability of occurring this by chance is less then 0.01. Another statistically significant correlation was identified between M-series tests results 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. In light of these two significant correlations, it seems that more intelligent students have better learning performance in web-based than in traditional learning environment.

No significant correlations were found between personality factors and learning outcome. Table 3 shows Pearson correlations of all psychological tests scores with background knowledge, learning outcomes and satisfaction with the system.

Conducting age and experience analysis we have found that Internet experience significantly correlates with learning outcome ($r = 0.37$, $p < 0.05$), as shown in Table 4, suggesting that students who spend more time on the Internet use web-based learning application more successfully than students who spend less time.

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 than less motivated students. Another statistically significant

Table 3. Correlations of personality and intelligence with knowledge and satisfaction

	Extroversion	Neuroticism	Intelligence
Background knowledge	-.182 p = .311	.066 p = .714	.393* p = .024
Learning outcome	-.088 p = .626	.184 p = .305	.465** p = .006
Satisfaction	.043 p = .810	.260 p = .143	.035 p = .845

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

Table 4. Correlations of age and experience with learning session results and satisfaction

	Age	Prior experience	Computer experience	Internet experience
Learning outcome	.333 p = .058	.284 p = .109	.180 p = .315	.370* p = .034
Satisfaction	.276 p = .120	.139 p = .441	.116 p = .521	.094 p = .602

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

correlation ($r = 0.35$, $p < 0.05$) was found between expectations from e-learning and satisfaction in using the system (SUS questionnaire). Apparently, users with grater expectations from the system have experienced higher levels of fulfillment in system usage. Those correlations are presented in Table 5, along with correlations for background knowledge. No significant connections were identified between background knowledge and other variables presented in this table.

Table 5. Correlations of motivation and expectations from e-learning with background knowledge, learning outcome and satisfaction

	Motivation	Expectations	Background knowledge
Background knowledge	.082 p = .648	.163 p = .364	
Learning outcome	.357* p = .041	-.026 p = .886	.314 p = .075
Satisfaction	.184 p = .306	.346* p = .049	.205 p = .251

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

3.3 Discussion

Personality factors, namely extroversion/introversion and the level of neuroticism, seem to have no impact on learning outcome (Table 3), the results which are in line with related literature, *cf.* [12, 13].

Considering motivation for e-learning and expectations from it, obtained results were expected (Table 5) – while motivation for e-learning is related to learning outcome, expectations from e-learning correlate with user satisfaction. In order to offer valuable results' interpretation, it is important to distinguish motivation from satisfaction. Motivation includes aspiration and effort to achieve a goal, while satisfaction refers to fulfillment we feel due to a goal achievement. Thus the obtained connection of expectations and satisfaction seems very natural.

Apparently, there is no connection between background knowledge and learning outcome. Such connection was expected because of the following reason. Namely, there are high correlations of background knowledge with all three dimensions of experience: prior experience ($r = 0.79$, $p < 0.01$), computer experience ($r = 0.44$, $p < 0.05$) and Internet experience ($r = 0.44$, $p < 0.05$). On the other hand, experience significantly correlates with learning outcome (Table 4). Consequently, the correlation of the background knowledge and learning outcome was also expected and such result would be in line with related studies [4]. 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 with the pre-test scores.

4 Conclusion

Appraising user characteristics that produce differences in learning performance has an important role when considering adaptive educational systems. The conducted empirical study reveals that there are significant connections of user intelligence, experience and motivation with her/his learning outcome in an e-learning environment. These results contribute to the knowledge base of user individual differences and they should be taken into account when developing a web-based instructional content.

Nevertheless, further work is required in order to determine the way in which relevant user characteristics could be exploited in enabling 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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