Working Memory Differences in e-Learning Environments: Optimization of Learners' Performance through Personalization

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Abstract. Working memory (WM) is a psychological construct that has a major effect on information processing, thus signifying its importance when considering individual differences and adaptive educational hypermedia. Previous work of the authors in the field has demonstrated that personalization on human factors, including the WM sub-component of visuospatial sketchpad, may assist learners in optimizing their performance. To that end, a deeper approach in WM has been carried out, both in terms of more accurate measurements and more elaborated adaptation techniques. This paper presents results from a sample of 80 university students, underpinning the importance of WM in the context of an e-learning application in a statistically robust way. In short, learners that have low WM span expectedly perform worse than learners with higher levels of WM span; however, through proper personalization techniques this difference is completely alleviated, leveling the performance of low and normal WM span learners.

Keywords: Adaptive Hypermedia, e-Learning, Working Memory, Individual Differences, User Profiling

1 Introduction

Individuals are characterized by numerous intrinsic traits and states, which relate to their learning performance. Chamorro-Premuzic and Furnham report personality, IQ, fluid intelligence and approaches to learning as predictors of academic performance [1]; state-like individual differences, such as anxiety, have been found to mediate the effect of trait-like differences [2], while Lau and Roeser identified groups of students that exhibit consisted academic performance in relation to their motivation and numerical, verbal and spatial cognitive abilities [3]. Among intelligence and motivation, working memory (WM) is also a predictor of performance [4].

Personalized educational systems have indeed emerged in the field of adaptive hypermedia [5,6,7,8], sharing a common research interest on the construct of learning style. Style is placed between personality and cognition [9], defining classifications of learners (see Cassady's overview of learning style theories [10]); still, neither of the cognitive, motivational or state-like factors influencing academic performance can be adequately addressed in such a generic way.

In an effort to build an adaptive educational system that incorporates psychological constructs that reflect individual differences, both trait and state-like, the authors presented a three-dimensional user representational model, which includes a) cognitive style [11], b) speed of processing, visual attention, WM, and c) emotional processing of the user [12]. Intelligence and fluid intelligence have deliberately been excluded, since it would be very complex to establish personalization rules- according to our opinion off course. Still, it is important to report that WM is correlated to general intelligence, at least to some extent [13,14].

In the context of empirically evaluating this model, personalization on the basis of cognitive style, visual WM and anxiety was proven to increase the performance of learners [15]. Still, the construct of WM was only partially approached and measured, especially when considering that it is one of the main predictors of performance in every aspect of learning [16]. This paper presents the authors subsequent work in the field of WM and personalization.

2 Theoretical Background, Hypotheses, and Implications

One of the predominant theories of WM is Baddeley and Hitch's multicomponent model [17]. According to Baddeley, "the term working memory refers to a brain system that provides temporary storage and manipulation of the information necessary for such complex cognitive tasks as language comprehension, learning, and reasoning" [18].

A brief description of the WM system is that is consisted of the central executive (CE) that controls two slave systems: a) the visuospatial sketchpad and b) the phonological loop. A later addition to the model is the episodic buffer that provides a temporary interface between the slave systems and the long term memory [19]. Both subsystems and the CE, which are generally independent from each other [20], have limited capacity.

The idea of exploring the role of differences in WM in the context of hypertext environments has indeed generated research [21,22], while Cognitive Load Theory is often used when referring to guidelines for designing hypermedia applications, related to WM span [23].

2.1 Hypotheses

Our research hypotheses were formed as follows:

i) Are WM measurements tools appropriate for the context of hypermedia learning?

ii) Do low WM learners perform worse than those with higher levels of storage capacity and CE function in a hypermedia learning environment?
iii) Would it be possible to level low WM learners' performance with their normal WM counterparts' through personalization techniques?

2.2 Classification and Personalization

The classification of users according to the two WM tests (visual memory and CE/verbal storage) was another issue of concern, since it would be possible for a user to perform significantly better in only one of the tests. The system however measured the aggregated performance of users' in both tests, albeit with additional considerations.

It should be clarified that our main concern is to identify users with low WM. The threshold that distinguishes medium from high WM individuals was known for the case of the visual test, but the modified CE/verbal storage test was not tested across a standard population. By conducting a pilot study, we adopted a relative threshold for identifying low WM individuals. Users who scored below the 1/3 of the aggregated score were classified as low WM learners, along with those who scored very low in one of the two tests, assuming that they lack the corresponding WM resources.

As it concerns the low WM personalized condition, the learning content was altered in two ways. Firstly, the simultaneously per webpage presented content was segmented. Fewer learning objects (images and paragraphs of text) were assumed to require less cognitive resources from users with limited storage capacity and attentional control.

The second method of personalization was the annotation of textual objects. This approach is partially derived from studies exploring the relationship of hypertext and WM [21]. Bold text and colors were used for important concepts, links and titles, in an effort to help learners organize information. In a sense, the system imposes on low WM learners a strategy of reading and organizing information; this was related, though not very closely, to the fact that strategies such as rehearsal have a positive effect on low WM learners [24].

3 Experimental Method

3.1 Design and Procedure

The experimental design was a between participants memory test. There were three groups of users: a) a control group of users with normal/high levels of WM, b) a group of low WM users who received the same with the control group on-line course and c) a group of low WM users who received a personalized course. All learning environments were personalized on learners' cognitive style.

The participants were students from the University of Cyprus, with their age varying from 18 to 21 years. The number of valid participants was 80 out of a total of 91 users; 11 were excluded due to very poor performance in the WM tests, which could imply failure to follow the tests' rules.

The subject of the e-learning procedure was an introductory course on algorithms. This course has also been used in our previous experiments, mainly because participants lack any previous knowledge on computer science. Immediately after the completion of the course, participants were asked to take a comprehension on-line test about what they had been taught. Their scores on this test was the dependent variable indicating academic performance.

3.2 Materials

In the case of visuospatial WM span, a tool was already available [25]; it only had to be implemented in the .NET platform of our environment.

The authors however were not aware of an electronic version of a phonological loop span and CE test. For that reason, we were provided with an extended Greek version of the listening sentence recall test of the WMTB-C [26]. For the electronic version of the test we opted for on-screen presentation of written sentences rather than auditory articulation.

This probably leads to a differentiated form of the original test, addressing perhaps different aspects of WM that those originally intended; still, by experimentally assessing the validity of the measurements, we expected that the relative classification of learners would be more appropriate for a web-environment.

4 Results

Low WM learners in the non-personalized condition performed worse, while the mean score of low WM learners in the personalized condition was not only equal but higher than that of the control group (normal/high WM learners). Specifically, low WM learners' score was 52% in the non-personalized and 67.4% in the personalized condition (15.4% increase of performance), while the control group achieved a 63.4% score.

This difference is statistically significant at zero level of confidence: a non parametric analysis of variance was performed, since the assumption of homogeneity of variances was not met: Welch statistic$_{(2, 47.980)}$=9.312, p=.000.

Post hoc analysis of variance (Tamhane's T2) revealed that the differences are statistically significant between the non-personalized low WM group and the other two; the personalized low WM group did not differ from the control group.

It should be noted that scoring in the two WM tests was not correlated. This is in line with the fact that the components of Baddeley and Hitch's model are relatively independent; otherwise, the validity of our measurements would be questioned. Additionally, there were absolutely no interactions or correlations of cognitive style with performance in WM tests or scoring.

5 Discussion

According to this research, individual differences in WM may partially predict the performance of users. Profiling users with respect to their WM capacity in order to provide them personalized instruction increased their level of comprehension. Considering that the difference in score reached 15.4%, attributed only to WM, a combined model of individual differences could possibly make a great difference in optimizing learners' performance in educational hypermedia.

There are however some limitations. The personalization rules were based on our assumptions; simple ideas often work, but considering the depth and numerous implications of WM, further research is needed to establish adaptive educational hypermedia design guidelines. Also, it remains ambiguous whether low WM learners where assisted more by the segmentation of the content or the annotation of the text. We also consider that there is still room for improvement in capturing electronically the WM capacity of users.

Nevertheless, our research hypotheses were confirmed, and the notion that WM is a key factor in e-learning was validated; instead of simply acknowledging this effect, it is possible to assist learners effectively, putting into practice the theoretical background of this construct.

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