Working Memory Span and E-Learning: The Effect of Personalization Techniques on Learners' Performance

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Abstract. This research paper presents the positive effect of incorporating individuals' working memory (WM) span as a personalization factor in terms of improving users' academic performance in the context of adaptive educational hypermedia. The psychological construct of WM is robustly related to information processing and learning, while there is a wide differentiation of WM span among individuals. Hence, in an effort to examine the role of cognitive and affective factors in adaptive hypermedia along with psychometric user profiling considerations, WM has a central role in the authors' effort to develop a user information processing model. Encouraged by previous findings, a larger scale study has been conducted with the participation of 230 university students in order to elucidate if it is possible through personalization to increase the performance of learners with lower levels of WM span. According to the results, users with low WM performed better in the personalized condition, which involved segmentation of the web content and aesthetical annotation, while users with medium/high WM span were slightly negatively affected by the same techniques. Therefore, it can by supported it is possible to specifically address the problem of low WM span with significant results.

Key words: Adaptive Hypermedia, Working Memory, User Profiling, Cognitive Psychology, Individual Differences

1 Introduction

Learning is related to a number of individual cognitive and affective trait and state-like characteristics, which account for the corresponding variability in learning performance. Constructs at different levels, such as IQ, fluid intelligence, personality and approaches to learning, have been reported as predictors of academic performance [1]; motivation along with numerical, verbal and spatial cognitive abilities have been related to specific patterns of academic performance [2], while state anxiety has been found to mediate trait-like individual differences [3]. The construct of working memory (WM) has also been identified as a predictor of learning performance [4, 5], while there are numerous studies that relate WM with learning and cognitive processes.

The research that is presented in this paper is focused on measuring learners' WM capacity, on examining the differences in performance in relation to WM resources, and finally on improving the performance of learners with lower levels of WM span. It should be mentioned that the authors have previously conducted relevant research, in an effort to build an adaptive educational system that incorporates psychological constructs that reflect individual differences. These differences, both trait and state-like, are represented by a three-dimensional user model, which consists of: a) cognitive style, b) speed of processing, visual attention, WM, and c) emotional processing [6]. This model aims to coherently combine preferences, abilities, trait and state-like characteristics, and to optimize the learning performance of users through mapping these characteristics on the instructional method.

The constructs of intelligence and fluid intelligence have deliberately been excluded, since it would be very complex, if not impossible, to establish personalization rules; the user profiling procedure would also be very burdensome, and perhaps assigning learners in groups according to their intelligence would raise ethical issues. On the other hand, WM is indicative of the cognitive abilities that are related to learning and correlated at some extent to general intelligence [7, 8].

As it concerns the empirical evaluation of the aforementioned user model, personalization on the basis of cognitive style, visuospatial WM and anxiety was proven to increase the performance of learners [9]. Still, the construct of WM was initially only partially approached and measured, while the methodology of the following experimental approach needed to be improved [10].

Within this context of ongoing experimental evaluation, this paper presents an extensive empirical study that was conducted in order to evaluate the role of WM span in educational hypermedia and, mainly, to assess the effectiveness of corresponding personalization techniques in terms of actually assisting learners with low levels of WM span in improving their performance.

2 Theoretical Background

One of the predominant theories of WM is Baddeley and Hitch's multicomponent model [11]. 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" [12].

Baddeley also refers to individual differences in the WM (digit) span of the population, thus providing a very good argument for using this construct as a personalization factor. Since WM is considered to be a predictor of academic performance, it would be of high importance to alleviate learning difficulties of learners with low levels of WM.

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 [13]. Baddeley's diagrammatical representation of the system is illustrated in Fig. 1.

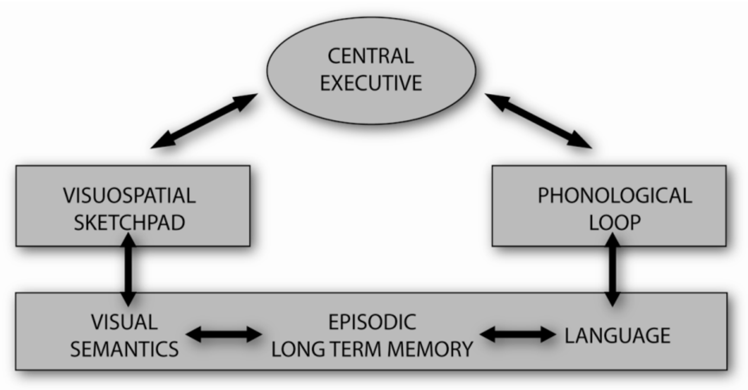

Fig. 1. Multicomponent model of WM

The CE is assumed to be an attentional-controlling system of limited resources; the visuospatial sketch pad manipulates visual images and spatial information, while the phonological loop stores and rehearses speech-based information and is necessary for the acquisition of both native and second-language vocabulary. The role of the episodic buffer is out of the scope of our research, which essentially is based on the original version of the model.

Both subsystems and the CE, which are generally independent from each other [14], have limited capacity. Though the number of items (or chunks) that can be stored in WM storage is dependent on various factors (such as length of words for example), individuals vary in their storage capacity (as mentioned above), the same way they vary in intelligence. In line with the notion of user profiling and satisfying users' needs, it could be argued that learners with low WM and CE capacity should be identified and instructed in a way that does not require manipulation of large chunks of information at the same time.

As it concerns the field of educational hypermedia, recent studies seem to establish a relation between WM resources and hypertextual learning. DeStefano and LeFevre [15] reviewed 38 studies that mainly address the issue of cognitive load in hypertext reading, showing that WM is often considered as a significant factor even at the level of explaining differences in performance. Lee and Tedder [16] examine the role of WM in different computer texts, and their results show that low WM span learners do not perform equally well in hypertext environments. Accordingly, McDonald and Stevenson [17] argue that non-linear hypertextual learning spaces are more demanding in WM resources in comparison to hierarchically structured environments. Also, Dutke and Rinck [18] have reported that certain tasks in multimedia learning require more WM resources, while individuals with lower levels of verbal and visuospatial WM capacity face increased difficulties.

Naumann et al [19] found that cognitive and metacognitive strategy training benefits learners with large WM capacity, “whereas the learning outcomes of participants with a small working memory capacity were deteriorated by both types of training.” Also, in relation to WM capacity, the term Cognitive Load Theory is often used especially when providing guidelines for designing hypermedia applications [20]; for example, in a very recent study that involved EEG measurements [21], it was found that leads in hypertext nodes may assist in decreasing cognitive load and on acquisition of domain and structural knowledge.

Based on the above, it could be argued that WM capacity (or span) may predict learning performance in hypertext environments, and that certain structures or methods of presentation are more demanding in WM resources. Consequently, in the context of adaptive educational hypermedia [22,23,24,25], WM span could constitute a significant user profiling and personalization factor, since: a) there are distinct differences with measurable effects among the learner population, and b) different hypertext structures and methods of presentation may benefit (or hamper) the performance of learners.

3 Research Questions and Design Implications

Learning in a hypermedia environment requires cognitive processing of visual and verbal content, involving both WM slave systems and CE resources. Hence, the first step would be the measurement of each learner’s visual and verbal working memory capacity with corresponding psychometric tests. Subsequently, an empirical evaluation of the performance of learners grouped according to their WM span levels and the use of personalization techniques would reveal if there are any significant differences.

It should be noted that our research interest is focused on learners with low levels of WM span; the main aim is to assist in the development of personalized instructional techniques that would ensure the effectiveness of adaptive educational hypermedia regardless of individual differences and abilities.

3.1 Research Questions

In the broader context of our research on WM and adaptive educational hypermedia, our research questions were the following:

i) Are WM capacity psychometric tools appropriate for the context of hypermedia learning?
ii) Do low WM learners perform worse than those with higher levels of memory capacity and CE function?
iii) Is it possible with the use of personalized instructional techniques to increase the performance of low WM learners?

3.2 Classification and Personalization

The classification of users according to WM span tests (visual memory and CE/verbal storage) was a main issue of concern. First of all, since these two measurements are independent, it would be possible for a user to perform significantly better in only one of the tests. However, considering that an e-learning course may as well contain both visual and verbal material, a more holistic approach in WM capacity would be more suitable for the needs of our approach. Consequently, the system profiled users on the basis of the aggregated performance in both tests, albeit with some additional considerations.

First of all, it should be reminded once more 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. As a result, we adopted a threshold that relatively identifies low WM individuals, after conducting a pilot study.

In terms of scoring, there was a complete analogy between the two tests by transforming the scores. Those that did not exceed the 1/3 of the aggregated score were classified as low WM learners. Regardless however of the total score, users that scored very low in one of the two tests were also classified as low WM learners, assuming that they lack the corresponding WM resources.

As it concerns the low WM personalized condition, which is a challenge of its own, the learning content was altered in two ways. Firstly, the content presented simultaneously on one webpage was segmented. A decreased number of learning objects (images and paragraphs of text) was assumed to require less cognitive resources from users with limited storage capacity and attentional control, allowing them to keep a more gradual pace on information processing. Initially, light-weighted versions of the pages are given to the users with low WM span and then, by clicking on the screen, the page unfolded at its full extent, with the remaining learning objects being presented to the user. This rather simple approach was proven effective in our previous experiments, possibly due to the fact that this gradual assimilation of information reduces the risk of cognitive overload.

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 [15]. It seems that diagrammatical representations and highly structured texts assist low WM users; thus, at the level of better structuring the text, different colors were used for annotating paragraph titles, distinguishing in parallel different sections of the page. 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; the assumption that this would be proven beneficial is related, though not very closely, to the fact that strategies such as rehearsal have a positive effect on low WM learners [26].

It should be clarified that both these methods are innovative and quite explorative, in the absence of well defined guidelines for improving the performance of low WM individuals. The literature over the implications of WM in every aspect of information processing is truly exhaustive, but the idea of leveling the performance of individuals despite their differences in cognitive abilities seems out of the scope, to our knowledge, of most prior research.

We definitely acknowledge that our approach is assumptive, but considering the lack of previous endeavors in exploring adaptive educational hypermedia and WM and in optimizing the performance of low WM learners, we rely on our experimental results in order to validate our methods.

4 Experimental Method

4.1 Design and Procedure

The design of the study was a single-factor, between-participants design, involving four groups of users: a) a group of low WM users that received a personalized course, presumably suitable for them, b) a group of low WM users who received a standard, non-personalized course, c) a control group of users with normal/high levels of WM who received the standard on-line course, and d) a control group of normal/high WM learners who received an on-line course that was personalized on the needs of low WM learners (same environment with group a). The dependent variable was learners' scores in an exam that followed the on-line course.

All versions of the learning environment were personalized on learners' cognitive style, in order to control for the impact of this factor on performance; our previous experimental results demonstrated that matching the instructional style to users' cognitive style positively affects performance, while mismatching has an adverse effect [9]. Hence, in order to control for any possible effects of matching or mismatching the instructional style to learners' preferences, the system provided personalized on style environments to all participants, based on Riding's Cognitive Style Analysis [27].

The participants were Greek speaking students from the Universities of Athens and Cyprus, 65% female and 35% male, with their age varying from 18 to 21 years. The number of valid participants was 230 out of a total of 260 users; 30 participants were excluded due to very poor performance (near zero scores) in the WM tests and the exam, which could imply either failure to follow the tests' rules or complete lack of interest. Participation in the experiment was voluntary.

The mean duration of the procedure was approximately one-hour, though there were not any time constraints imposed on learners. The data were gathered from three consecutive identical experiments: two were conducted in a computer science laboratory in Cyprus and one in Athens, with approximately 15 participants in each session.

Each user logged in the system, took the cognitive style and WM assessment tests, and was quasi-randomly assigned into one of the aforementioned groups; thereafter the learner was navigated to the e-learning course. 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 of 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 (maximum possible score=100).

4.2 WM Span Measurement Considerations and Tools

The first step in setting up our experiments was to measure users' WM with the appropriate psychometric tools. Integrating such measurements in an adaptive hypermedia system through a user profiling procedure essentially requires the development of electronic versions of pencil and paper tests. In the case of visuospatial WM span, a tool was already available [28]; 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 [29]. This test measures both the CE function and the verbal storage ability, providing an indication of individuals' WM ability. In its original form, it is a pencil and paper listening test; in the case of e-learning though information is usually conveyed through written text. For that reason, we were mainly interested in learners' ability to manipulate written and not acoustic verbal information; this is why in 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 than 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, focusing on storage of written verbal material and CE function in front of a computer screen. A brief description of test follows, for the purposes of clarifying how the test was adapted in our system.

Users are required to store the last word of a series of consecutively presented (written) sentences, while deciding at the same time whether the meaning of each sentence makes sense or not. The test gradually becomes more difficult, since the number of sentences increases from two (first level) to nine (last level). There are six series of sentences in each level, and users have to remember correctly the last words of four at least series in order to proceed to the next level.

At the third level, for example, four sentences are presented one after the other, each remaining on screen for two seconds. Users have to decide if the meaning of each sentence is true of false, by pressing the corresponding key, triggering the presentation of the next sentence. When all sentences are presented, users are asked to fill a corresponding number of text fields with the last word of each sentence. Scoring is the same as in the original test.

5 Results

The mean scores of the four groups of learners demonstrate that the personalization techniques that were employed (segmentation of the content and annotation) benefited learners with low WM span; in contrast, these techniques had a slightly negative effect on learners of the control group (see table 1). A one-way analysis of variance was performed on the data (since the assumptions of normality and homogeneity of variances were met), revealing that this difference is statistically significant: $F_{(3,226)}=3.930$, $p=0.009$.

Table 1. Mean Scores of Learner Groups

Condition	N	Mean Score	Std. Deviation
Personalized Low WMS	46	59.17	15.71
Non-personalized Low WMS	47	50.27	14.06
Non-Personalized Control Group	87	59.46	16.15
Personalized Control Group	50	55.94	16.40
Total	230	56.76	16.01

A post hoc analysis (Tukey HSD) revealed that the difference in scores is statistically significant between the three first groups (see table 2); the personalized control group did not differ significantly from any other group, which was expected since learners' scores in this condition were close to the total mean.

Table 2. Post Hoc Analysis of Learner Groups' Scores

Tukey HSD

(I) Condition	(J) Condition	Mean Difference (I-J)	Significance
Personalized Low WMS	Non-personalized Low WMS	**8.90***	**0.034**
	Non-Personalized Control Group	-0.29	1.000
	Personalized Control Group	3.23	0.745
Non-personalized Low WMS	Non-Personalized Control Group	**-9.18***	**0.008**
	Personalized Control Group	-5.66	0.289
Non-Personalized Control Group	Personalized Control Group	3.52	0.588

According to these findings, it is shown that:

- Learners with medium/ high levels of WM performed better than those with low levels of WM, in the same non personalized environment (+9.2 points). Thus, WM has an effect on users' performance in educational hypermedia.

- Learners with low WM improved their performance in the personalized condition by 8.9 points, reaching the performance of medium/high WM learners (only -0.29 points difference).
- The personalization method that was employed had no positive effect on learners with medium/high levels of WM; on the contrary, though statistically non significant, these learners had lower scores than those of the non-personalized control group (-5.7 points), though still better than non-personalized low WM learners (+3.5 points). Hence, it may be argued that the segmentation and annotation techniques address directly the low WM span issue and do not generally improve the method of presentation.

Additionally, the scores of the two WM span tests were 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 the measurements would be questioned.

6 Discussion

According to the findings of this study, our research questions were answered as follows: i) the measurement of WM with electronic versions of psychometric tools reflects users' cognitive ability in hypermedia environments, ii) low WM learners perform worse than those with higher levels of memory capacity, and iii) certain personalization techniques may assist low WM learners in optimizing their performance, reaching the levels of those with higher WM.

Therefore, it seems that less simultaneously presented learning content and structuring the text with annotations seemed to address the issue of limited storage and attentional control efficiently. It should be noted that these techniques do not positively affect all learners, but specifically address the limitations of low WM span.

There are however some limitations in our study. First of all, the personalization rules were based on our assumptions; even if the results justify this approach, there should be a large scale evaluation of the proposed adaptation techniques. Simple ideas often work, but considering the depth and numerous implications of WM, further research is needed to establish a robust set of adaptive educational hypermedia design guidelines.

Also, it remains ambiguous whether low WM learners were assisted more by the segmentation of the content or the annotation of the text. Both techniques were employed in the personalized condition, and it is impossible to distinguish separate effects. Segmentation of the web page was proven significant in our previous work with visual WM span, albeit with smaller effect. Annotation of the text may also have been useful, but since in this experiment we also measured verbal storage and CE capacity, perhaps identifying a larger number of low WM learners increased the positive effect of segmentation; the effect of annotating the text should be separately examined.

The way we incorporated WM measurement tools in our system was mainly affected by the needs of our research in adaptive hypermedia. First of all, we focused on written text verbal storage and CE function, than auditory; additionally, instead of using a battery of WM tests that examine this construct in depth, we measured what we believed was adequate for our exploratory approach, without posing difficult and time consuming challenges to users. Still, we consider that there is room for improvement in capturing electronically the WM capacity of users. For example, a backward word span task (demanding users to recall words in the reverse order) would increase the validity of the measurements and provide a better insight on learners' abilities.

Nevertheless, all our research questions were answered in a way that supports our approach, and the notion that WM is a key factor in e-learning was validated. Moreover, instead of simply acknowledging this effect, it was shown that it is possible to assist learners effectively, putting into meaningful practice the theoretical background of this construct. This encourages us to continue research on our model, incorporating individual differences theories in the field of adaptive e-learning. Future work on this line of research includes the measurement of state-like user characteristics, especially those related to emotional processing. Real time biometric techniques have already been included in our experiments, and in parallel with the aforementioned WM findings, further optimization of learners' performance is anticipated.

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