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Prior Knowledge and Cognitive Styles in Personalized Learning

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Abstract: In the past decade, a number of personalized learning systems have been developed. Prior knowledge has widely been considered in the development of personalized learning systems. On the other hand, previous research suggested that cognitive styles have great effects on student learning. To this end, this study examine how cognitive styles, affect learners' reactions to a personalized and non-personalized learning systems based on learners' prior knowledge. Forty-four undergraduate and postgraduate students participated in this study. The results show that Serialists show positive reactions to the personalized learning system while Holists demonstrate equal reactions to the personalized learning system and the non-personalized learning system. The implications of these results for the design of personalized learning systems are discussed.

Keywords: Cognitive Styles, Personalization, Prior Knowledge

1. Introduction

Web-based learning systems provide students with multiple ways so that they can develop their own learning approaches. This may be the reason why Web-based learning systems are so popular in educational settings [20]. The reason for such popularity is that the Web-based learning systems offer many advantages over traditional classroom-based training. On the other hand, there is great diversity among learners, who may have heterogeneous backgrounds, in terms of their knowledge, skills and needs [4]. Moreover, learners who have various backgrounds may prefer to interact with the Web-based learning systems with different ways [4]. Thus, there is a pressing need for the development of Web-based learning systems that can support the preferences of each learner [2]. To address this issue, personalization is widely used in the field of Web-based learning. Personalization tailors content, structure and/or presentation to match the preferences of each individual according to his/her characteristics and needs [25] [14] [16]. However, the delivery of personalization is complex because the adaptation to each individual requires the understanding of his/her preferences[1] and prediction of his/her behavior [9]. Therefore, understanding each learner's preferences is an essential issue for the delivery of personalization.

As showed in the previous discussion, students have diverse preferences when using the Web-based learning system. Thus, human factors play an important role in the development of the Web-based learning systems, ranging from prior knowledge [15] [19] to cognitive styles [3] [7]. Among various characteristics, prior knowledge is predominant in personalization, especially for Web-based learning [27]. Empirical evidence has suggested that personalizing Web-based learning systems based on learners' prior knowledge can improve their learning performance [10] [23] [28]. Such systems are useful because they can deliver tailored services in a way that will be most appropriate and valuable to the learners [2]. However, they mainly focus on prior knowledge and ignore the effects of other human factors.

In addition to prior knowledge, cognitive styles also play an essential role in Web-based learning and affect each individual's learning preferences and behavior [5]. Thus, it is not sufficient to provide effective personalization to take into account prior knowledge. In other words, cognitive styles should also be taken into account in the delivery of personalization. Within the area of cognitive styles, Witkin's Field Dependence [29] has emerged as one of the most widely studied human factors. Witkin's Field Dependence has a conceptual link with the other dimension of cognitive style, i.e., Pask's Holism/Serialism. Jonassen and Grabowski [17] describe Holists as preferring to process information in a 'whole-to-part' sequence. However, the different preferences between Field Dependent and Field Independent users can be divided more clearly and logically than the differences between Holists and Serialists. In other words, identifying the different preferences of Holists and Serialists is more complex. To this end, this study investigates Pask's Holism/Serialism, instead of Witkin's Field Dependence.

In summary, the study presented in this paper attempts to investigate personalized Web-based learning systems from the perspective of multiple human factors. In harmony with the main stream of personalization, this study develops a personalized Web-based learning system based on learners' prior knowledge and then examines how cognitive styles affect learners' reactions to this personalized Web-based learning system. The ultimate aim of this study is to incorporate both prior knowledge and cognitive styles into the delivery of personalization because these two human factors are widely applied in the delivery of personalization [22]. Thus, the outcome of this study can not only be used to improve the development of personalized Web-based learning systems, but also provide concrete solutions to personalize other Web-based applications, such as online shopping and search engines. By doing so, the quality of these applications can be improved.

2. Methodology Design

To effectively achieve the aforementioned aim, an empirical study was conducted. This section describes the methodology design of the empirical study, including participants, research instruments, experimental procedures and data analyses.

2.1 Participants

Previous research indicated that there is a need to investigate how to provide additional support for low-prior knowledge learners [6]. Thus, this study focuses on low-prior knowledge learners. More specifically, 44 undergraduate and postgraduate students from some universities in Taiwan participated in our study voluntarily. A request was issued to students in lectures, and further by email, making clear the nature of the studies and their participation. All participants had the basic computer and Internet skills necessary to use a Web-based learning system but they do not any understanding of the subject content of the Web-based learning system described in Section 2.2.1.

2.2 Research Instruments

The research instruments used in this study included (1) two Web-based learning systems used to teach students "Interaction Design", (2) Study Preferences Questionnaire used to measure students' cognitive styles, (3) task sheet used to describe practical tasks that students need to do when interacting with the Web-based learning systems, and (4) post-test used to assess how students have learnt after using the Web-based learning systems.

2.2.1 Web-based Learning Systems

In this study, two Web-based learning systems are developed. Both of them give an introduction to Interaction Design and provide two kinds of navigation tools. One is Keyword Search, which allows learners to locate specific information based on their particular needs. The other one is Hierarchical Map, which provides a global picture of the subject content. Nevertheless, these two Web-based learning systems provide personalization for learners with different levels of prior knowledge. One is for low prior knowledge learners, i.e., a personalized learning system, while the other is for high prior knowledge, i.e., a non-personalized learning system.

The design rationale of the two Web-based learning systems is based on a framework proposed by Chen, Fan and Macredie [6]. Learners with low prior knowledge lack sufficient understanding of subject content so there is a need to provide them with simple design and more visual cues. Thus, the personalized learning system provides a single keyword search so that the learners can make a simple query. Furthermore, keywords searched are highlighted with yellow color in the display of the results so that learners can easily identify whether results are relevant. Additionally, there is a simple tree map (Figure 1), with which learners can construct knowledge step by step. Conversely, learners with high prior knowledge have a great deal of the understanding of subject content so they can accept sophisticated design and fewer visual cues. Therefore, the non-personalized learning system provides multiple keyword search with Boolean operators. Keywords are not highlighted but there is a complete tree map (Figure 2), with which learners can jump from one section to the other section directly.

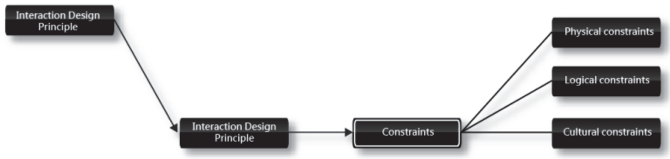

Figure 1. Hierarchical Map (Personalized learning system).

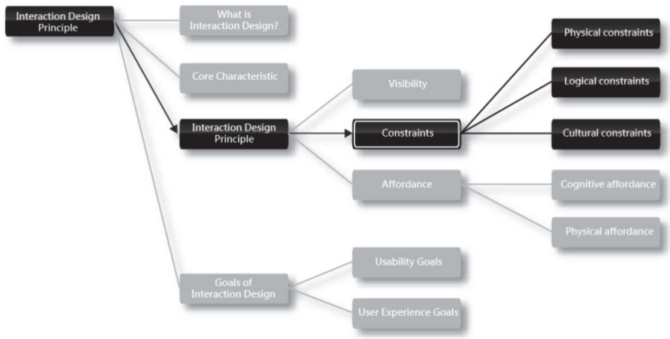

Figure 2. Hierarchical map (non-personalized learning system).

2.2.2 Task Sheet

When interacting with the Web-based learning systems, the participants were given a task sheet, which described the tasks that learners need to perform. To reduce the bias of this study, there are two different kinds of tasks. One is a factual question while the other is an essay question. The former focuses on a single concept and there is only one standard answer for the question. The latter includes multiple concepts so learners have to realize the relationships of various keywords described in the questions. Learners need to complete these two kinds of tasks. The starting time and the end time for each student were recorded.

2.2.3 Post-test

The post-test was designed to assess how much they have learnt from the Web-based learning systems. The post-test was presented in a computer-based format and included 20 multiple-choice questions. Each question included three different answers and an “I don’t know” option but there was only one right answer. The questions covered all eight sections of the Web-based learning program from basic concepts to advanced skills. Students were allotted 20 minutes to take the post-test and were not allowed to examine the content presented in the system at the same time.

2.2.4 Study Preferences Questionnaire (SPQ)

As suggested by Section 1, further empirical studies are needed to examine the differences between Holists and Serialists so the study presented in this paper investigates Holism/Serialism, instead of Field Dependence/Independence. In an attempt to devise a relatively quick and easy measure of Holist and Serialist biases, Ford [12] developed the Study Preferences Questionnaire (SPQ), which is an 18-item inventory for categorizing learners as Holists or Serialists. In this vein, students were provided with two sets of statements. They were asked to indicate their degree of agreement with either statement or to indicate no preferences [12]. As the SPQ has been used in several studies [8] [11] [13] [26], it was chosen for this study, which identified Holists and Serialists by using criteria suggested by the original producer [12]: (a) if users agree with over half of the statements related to Holists, they are identified as Holists; (b) if users agree with over half of the statements related to Serialists, they are then considered as Serialists, and (c) if users agree with half of the Holist statements and half of the Serialist Statement, they are then considered as Intermediate. The reliability of the SPQ is adequate ($\alpha = 0.67$) [21].

2.3 Experimental Procedures

There were two scenarios in this study. One is a personalized scenario, in which learners used a Web-based learning system that matched with their prior knowledge. The other is a non-personalized scenario, in which learners used a Web-based learning system that did not match with their prior knowledge.

Regardless the personalized scenario or non-personalized scenario, learners need to complete the tasks when they interact with the Web-based learning systems. After finishing the tasks, they were required to go into the final step, i.e., the post-test. They needed to take the post-test to evaluate how much they have learned from the Web-based learning systems, which is regarded as their learning performance.

2.4 Data Analysis

In this study, seven attributes were analyzed with data mining techniques, including (1) the total time used for keyword searching, (2) the frequencies of using keyword searching, (3) the total number of movements made, (4) the total number of repeated visiting, (5) the total number of visited pages, (6) the number of pages in each keyword searching, and (7) the number of pages visited each second.

Among various data mining techniques, K-means was used to conduct data analyses for this study because it was widely used to analyze learners' on-line learning behaviors. In particular, our recent studies [7] found that K-means is a useful tool to cluster learners' behavior. However, a major limitation of using the K-means algorithm is that the number of clusters needs to be predefined. In other words, there is a need to identify the most suitable number of clusters to perform the K-means algorithm. Such an issue can be treated as parameter exploration [18], which is used to decide the suitable value of parameters. The parameter exploration is useful when a dataset is not large. Thus, the K-means algorithm is suitable for this study because the dataset was not large. Therefore, the parameter exploration was applied to decide the parameters of the K-means algorithm in this study.

3. Results and Discussion

3.1 Overview

As indicated in Section 2.4, seven attributes were considered in data analyses. The data obtained from these seven attributes had been normalized firstly before utilizing the K-means algorithm because these attributes are not comparable. More specifically, a big difference exists among the range of these attributes. Subsequently, the clusters are created with the K-means and they are divided into two groups, i.e., the personalized scenario and non-personalized scenario, each of which has four clusters. After carefully examining the details of the clusters in each scenario, we found that one cluster can be treated as outliers in each scenario because there are few number of cases. Therefore, only three clusters are used for further investigation in each scenario.

Furthermore, we found that two attributes show differences among the three clusters for each scenario, i.e., the number of pages visited for each keyword search (page/keyword) and the number of pages visited per second (page/task time). Additionally, we also examine corresponding features of each cluster, including post-tests scores, task time and cognitive styles.

3.1.1 Personalized Scenario

Three clusters are applied for the investigation of this scenario. Cluster 1 is the major cluster, which includes almost half of the participants. The trend of each cluster is described below.

C1 (N=10): The number of pages read with each keyword search (page/keyword) is higher than the number of pages read per second (page/task time) and they get the best post-test score (Mean=10.40; Standard Deviation=2.59), regardless the personalized or non-personalized scenario.

C2 (N=6): The trend of this cluster is similar to Cluster 1 in the personalized scenario. However, learners get the lowest post-test score (Mean=9.67; Standard Deviation = 3.61)among the three clusters in the personalized scenario.

C3 (N=5): The trend of Cluster 3 is similar to Cluster 1 and Cluster 2. However, learners in Cluster 3 spend the longest task time (Mean=0.31; Standard Deviation = 0.07) among the three clusters of the personalized scenario.

3.1.2 Non-Personalized Scenario

Like the Personalized Scenario, there are also three clusters considered in the non-personalized scenario. The trend of each cluster is described below:

C1 (N=5): The number of pages read with each keyword search (page/keyword) is lower than the number of pages read per second (page/task time) and they get the best post-test score (Mean=9.60; Standard Deviation = 1.34) among the three clusters of the non-personalized scenario.

C2 (N=7): The trend of this cluster is similar to Cluster 1 in the non-personalized scenario. However, the post-test score (Mean=8.57; Standard Deviation = 3.95) is not only the lowest one in the non-personalized scenario, but also the lowest score among the six clusters. The majority of females appear in this cluster.

C3 (N=7): The trend of Cluster 3 is similar to Cluster 1 and Cluster 2. However, learners in this cluster spend the longest task time (Mean=0.50; Standard Deviation = 0.27), regardless the personalized or non-personalized scenario.

3.2 Learning Performance

This section compares the differences between students' learning performance in the personalized scenario and those in the non-personalized scenario. To address such an issue, the students' post-test scores and task time were used to evaluate their learning performance.

Regarding the post-test score, students in the personalized scenario performed better than those in the non-personalized scenario (Figures 3 to 5). In other words, students can benefit from the personalized scenario to get high post-test scores whereas they may obtain low post-test scores in the non-personalized scenario. In this study, the personalized scenario provides a simple interface while the non-personalized scenario presents a complex interface. This finding suggests that the simple interface is suitable for students with low prior knowledge to help them learn an unfamiliar topic, which in turn, they can obtain high performance. Conversely, the complex interface in the non-personalized scenario can not only make students obtain low performance in the post-test, but also let students waste much time in an unsuitable environment.

Regarding task time, the students in the personalized scenario spent less time completing the tasks than those in the non-personalized scenario (Figure 6). It means that students in the personalized scenario can not only get a high post-test score, but also can use an efficient way to complete their tasks. The results echoes those from the post-test scores, which indicated personalizing instructional material to matches with learners' characteristics can help learners not only achieve good performance but also accomplish their tasks in an efficient way.

After examining Figure 7 and Figure 8, we found that learners among the three clusters in the personalized scenario spend similar amount of time completing the tasks. In other words, there is no big difference among the three clusters. However, there are big diversities among the three clusters in the non-personalized scenario. Leaners in Cluster 2 spent the least amount of task time while those in Cluster 3 spent the most amount of task time, regardless the personalized or non-personalized scenario. It implies that not all of the learners can overcome the challenges caused by non-personalization so unpredictable task time exists in the non-personalized scenario.

3.3 Cognitive Styles

In addition to overall learning performance, we also examined how Holists and Serialists react differently to the personalized scenario and the non-personalized scenario.

3.3.1 Serialists

Regarding the personalized scenario, learners in Cluster 2 and Cluster 3 got lower post-test score. On the other hand, few Serialists appear in these two clusters (Figure 9). Regarding the non-personalized scenario, learners in Cluster 2 and Cluster 3 got lower post-test score. On the other hand, most Serialists appear in these two clusters (Figure 10). These results suggest that the non-personalized scenario has negative effects on Serialists. This is probably because the non-personalized learning system provides a complex keyword search, which can be used to combine to search different keywords. This design approach does not support the needs of Serialists, who focus on only one thing at a time.

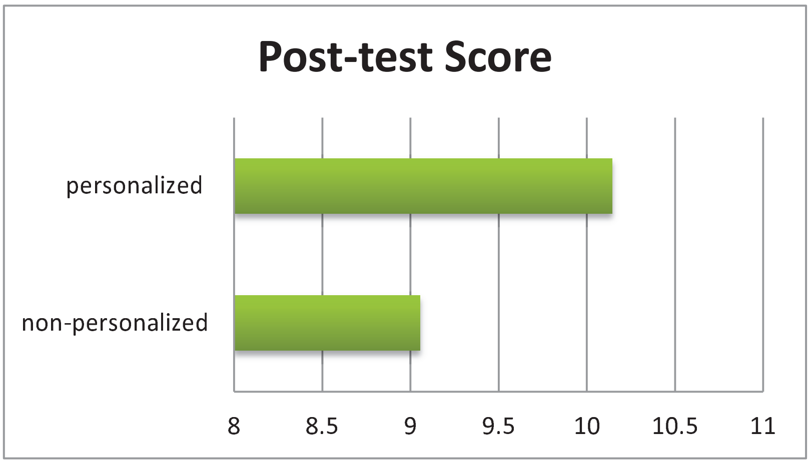

Figure 3. Post-test score (overall).

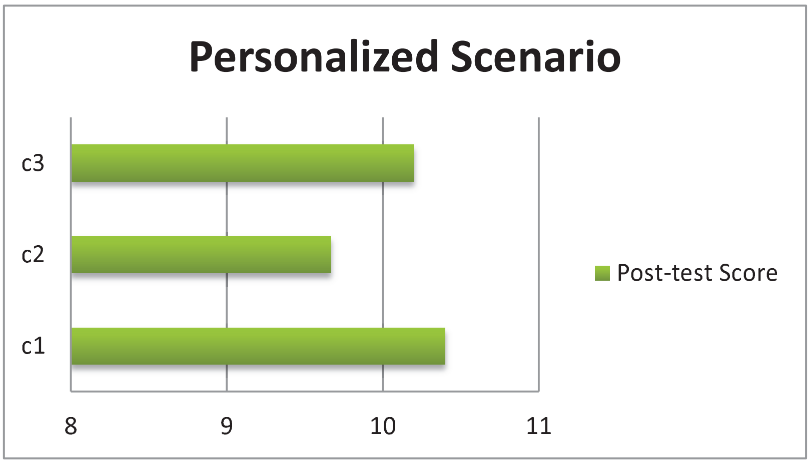

Figure 4. Post-test score (personalized scenario).

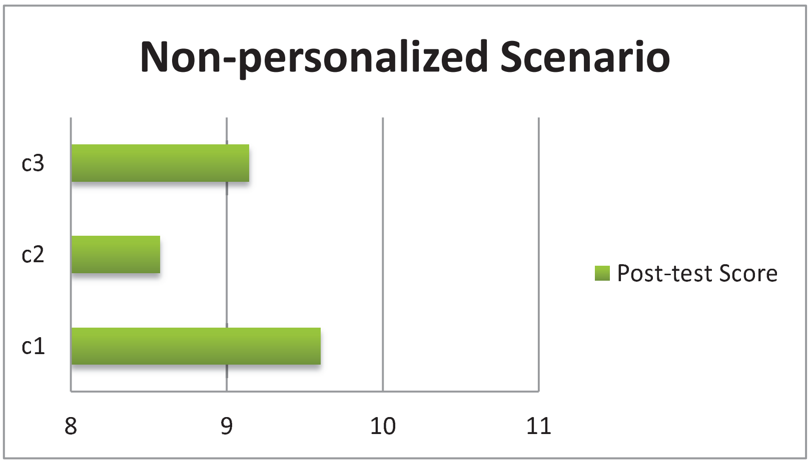

Figure 5. Post-test score (non-personalized scenario).

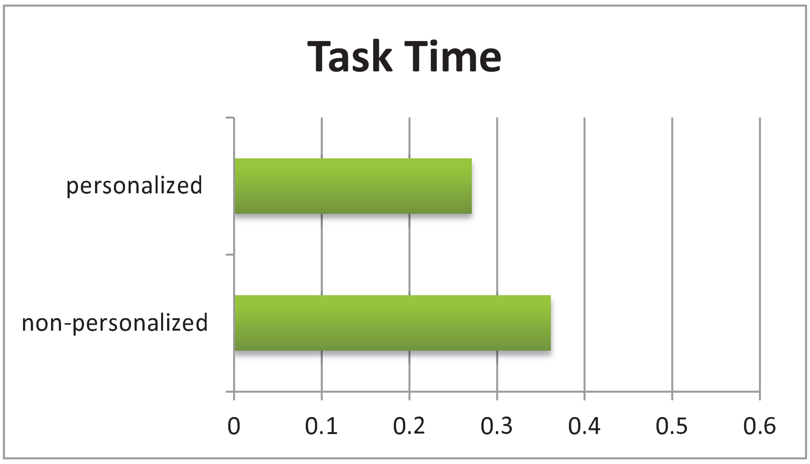

Figure 6. Task time (overall).

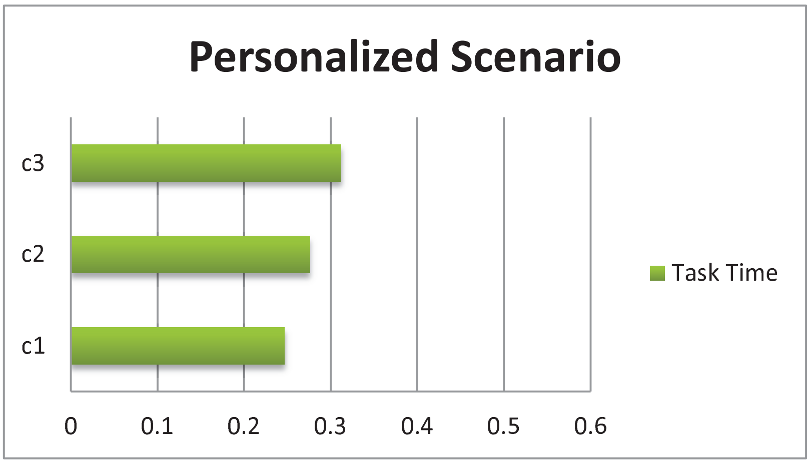

Figure 7. Task time (personalized scenario).

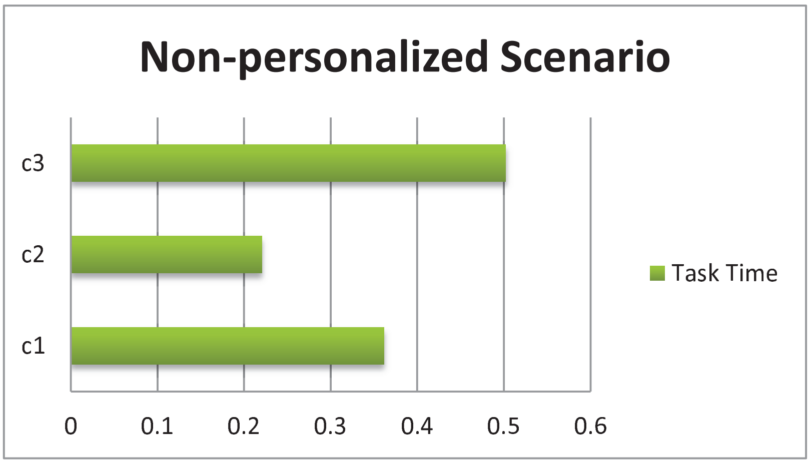

Figure 8. Task time (non-personalized scenario).

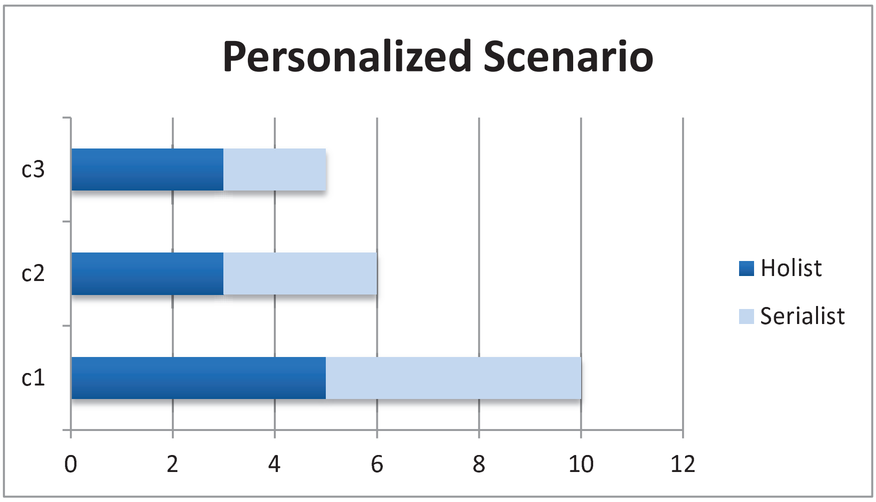

Figure 9. The distribution of Serialsts and Holists in personalized scenario.

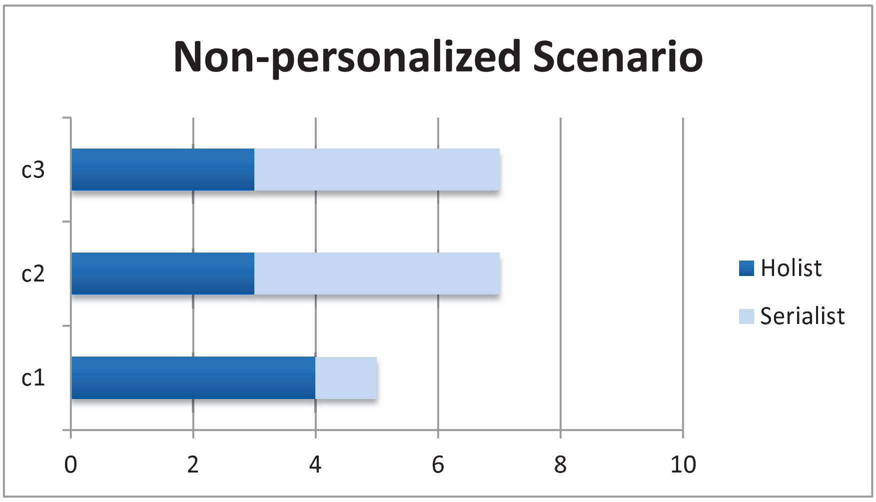

Figure 10. The distribution of Serialsts and Holists in non-personalized scenario.

3.3.2 Holists

As showed in Figures 9 and 10, Holists are evenly distributed in the three clusters, regardless the personalized scenario and the non-personalized scenario. In other words, the Holists do not show strongly different reactions to the personalized scenario and the non-personalized scenario. Only a simple keyword search and a partial hierarchical map are provided in the personalized learning system, where learners can merely get a local picture, instead of an overall picture. In theory, this scenario, thus, cannot satisfy the needs of Holists, who would like to get a global view. However, the aforementioned results suggest that Holists have potential to overcome difficulties that they meet in the personalized scenario. This is probably because the

flexibility is included in the personalized learning system. More specifically, hypertext links are applied to connect other main categories and related categories and the hierarchical map is clickable. Thus, the Holists can gradually get the global picture by following the hypertext links or clicking the hierarchical map.
The results presented in Section 3.3.1 and Section 3.3.2 suggest that the personalized learning system can match with the needs of both Holists and Serialists. Thus, Web-based learning systems should not only provide a simple keyword search and a hierarchical map that show a local picture, but also should make best of hypertext links and clickable hierarchical maps so that the needs of different cognitive styles can be accommodated.
The abovementioned findings suggest that Serialists and Holists show different preferences. More specifically, Serialists show positive reactions to the personalized scenario while Holists demonstrate equal reactions to the personalized scenario and the non-personalized scenario. Figure 11 proposes a framework, which summarizes the findings of this study.

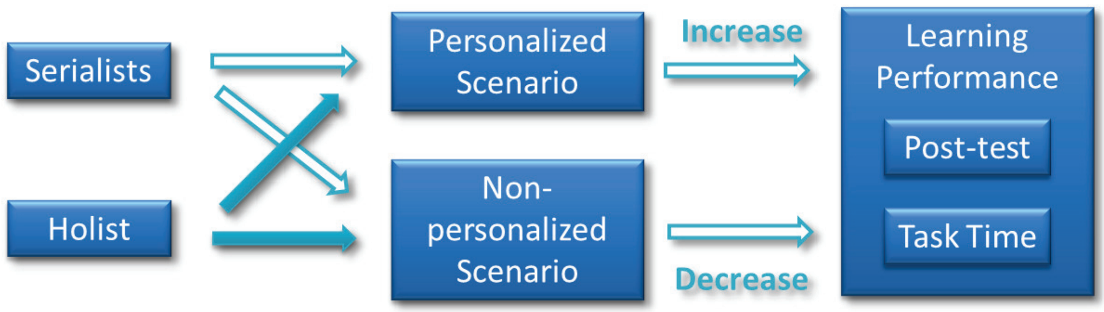

Figure 11. A framework based on the findings of this study.

4. Conclusions

This study examines learners' reactions to the personalized scenario and the non-personalized scenario based on their prior knowledge. In addition, this study also investigates how Holists and Serialist react differently to these two scenarios. Our results demonstrated that the non-personalized scenario has negative effects on Serialists while Holists have potential to overcome difficulties that they meet in the personalized scenario. In brief, Serialists have relatively strong reactions to the personalized learning system based on prior knowledge. The findings described in this paper have shown the importance of understanding the effects of multiple human factors on personalization and non-personalization.
However, this was only a small-scale study. Further work needs to be undertaken with a larger sample to provide additional evidence. Another limitation of these studies is that this study only uses a k-means algorithm to conduct data analyses so further works can consider other data mining algorithms to discover more hidden relationships. Moreover, there is a need to consider other human factors in future. More specifically, this study investigate how cognitive styles affect learners' reactions

to a personalized learning system based on learners' prior knowledge. Further works can develop personalized learning systems on the basis of gender differences or cognitive styles and then examine how other human factors affect students' reactions to this personalized learning system. In addition, the results of such works could be integrated with those of this study to build robust user models for the development of effective personalized learning systems that can accommodate learners' individual differences.

REFERENCES

[1] Ardissono, L., Goy, A., Petrone, G., & Segnan, M. (2005). A multi-agent infrastructure for developing personalized web-based systems. *ACM Transactions on Internet Technology, 5(1),* 47–69.

[2] Berkovsky, S., Kuflik, T., & Ricci, F. (2008). Mediation of User Models for Enhanced Personalization in Recommender Systems, *in User Modeling and User-Adapted Interaction,* 18(3), 245-286.

[3] Calcaterra, A., Antonietti, A., & Underwood, J. (2005). Cognitive style, hypermedia navigation and learning. *Computers & Education,* 44(4), 441–457.

[4] Chen, S. Y., & Macredie, R. D. (2004). Cognitive Modelling of Student Learning in Web-based Instructional Programmes. *International Journal of Human-Computer Interaction,* 17(3), 375-402.

[5] Chen, S. Y., & Macredie, R. D. (2010). Web-based Interaction: A Review of Three Important Human Factors. *International Journal of Information Management,* 30(5), 379-287.

[6] Chen, S. Y., Fan, J., & Macredie, R. D. (2006). Navigation in hypermedia learning systems: Experts vs. novices. *Computers in Human Behavior,* 22(2), 251–266.

[7] Chen, S.Y., & Liu, X. (2008). An integrated approach for modeling learning patterns of students in web-based instruction: a cognitive style perspective. *ACM Transactions on Computer-Human Interaction,* 15(1), Article 1.

[8] Clarke, J. A. (1993). Cognitive style and computer-assisted learning: problems and a possible solution. *Association for Learning Technology Journal,* 1(1), 47–59.

[9] Deshpande, M., & Karypis, G. (2004). Selective Markov models for predicting Web page accesses. *ACM Transactions on Internet Technology,* 4(2), 163–184.

[10] Dochy, F. J. R. C. (1992). *Assessment of prior knowledge as a determinant for future learning.* Utrecht/London: Lemma BV/Jessica Kingsley Publishers.

[11] Ellis, D., Ford, N., & Wood, F. (1992). *Hypertext and learning styles. Final report of a project funded by the Learning Technology Unit.* Sheffield: Employment Department.

[12] Ford, N. (1985). Learning styles and strategies of postgraduate students. *British Journal of Educational Technology,* 16(1), 65–79.

[13] Ford, N., & Chen, S. Y. (2000). Individual differences, hypermedia navigation and learning: an empirical study. *Journal of Educational Multimedia and Hypermedia,* 9(4), 281–312.

[14] Graf, S., & Kinshuk. (2008). Adaptivität in Lernplattformen unter Berücksichtigung von Lernstilen. *Zeitschrift für e-learning, Lernkultur und Bildungstechnologie, 3(3),* 40-51.

[15] Greene, J. A., Costa, L., Robertson, J., Pan, Y., & Deekens, V. M. (2010). Exploring relations among college students' prior knowledge, implicit theories of intelligence, and selfregulated learning in a hypermedia environment. *Computers & Education,* 55(3), 1027–1043.

[16] Jin, X., Zhou, Y., & Mobasher, B. (2004). A Unified Approach to Personalization Based on Probabilistic Latent Semantic Models of Web Usage and Content. Proceedings of the AAAI 2004 Workshop on Semantic Web Personalization (SWP'04) Held at AAAI 2004, San Jose, July 2004.

[17] Jonassen, D.H., & Grabowski, B. (1993). *Individual Differences and Instruction.* Allen & Bacon, New York.

[18] Jong, K. A. D. (1975). Analysis of the behavior of a class of genetic adaptive systems. *Doctoral Dissertation*. The University of Michigan, Ann Arbor, MI.

[19] Lee, C., & Chen, M. (2009). A computer game as a context for non-routine mathematical problem solving: the effects of type of question prompt and level of prior knowledge. *Computers & Education,* 52(3), 530–542.

[20] Liu, C., Chiang, T., & Huang, Y. (2007). Assessment of effectiveness of Web-based training on demand. *Interactive Learning Environments,* 15(3), 217–235.

[21] Mampadi, F., Chen, S. Y., Ghinea, G., & Chen, M. P. (2011). Design of adaptive hypermedia learning systems: A cognitive style approach. *Computers & Education,* 56, 1003–1011.

[22] Minetou, C. G., Chen, S. Y., & Liu, X. (2008). Investigation of the Use of Navigation Tools in Web-based Learning: A Data Mining Approach. *International Journal of Human-Computer Interaction,* 24(1), 48-67.

[23] Moerkerke, G. (1996). *Assessment for flexible learning: Performance assessment, prior knowledge state assessment and progress assessment as new tools.* Utrecht/London: Lemma BV/Jessica Kingsley Publishers.

[24] Pask, G. (1979). Styles and strategies of learning. *British Journal of Educational Psychology,* 16(1), 128-48.

[25] Perugini, M. (2011). *European Journal of Personality*, 24(1), 1.

[26] Robertson, J.E. (1994). Information skills in further education: A hypertext approach to learning in business studies. PhD Thesis. Robert Gordon University.

[27] Surjono, H., & Maltby, J. (2003). Adaptive Educational Hypermedia based on Multiple Student Characteristics. *Lecture Notes in Computer Science,* 2783, 442-449.

[28] Weibelzahl, S. (2001). Evaluation of adaptive systems. *User Modeling: Proceedings of the Eighth International Conference,* UM2001 (292–294). Berlin: Springer.

[29] Witkin, H. A., Moore, C. A., Goodenough, D. R., & Cox, P. W. (1977). Field-dependent and field independent cognitive styles and their educational implications. *Review of Educational Research,* 47(1), 1–64.