Evaluation of Mobile Learning: A Cognitive Style Approach

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Abstract: Mobile devices bring a lot benefits to student learning, including flexibility, convenience and ubiquity. On the other hand, students have various characteristics, among which cognitive styles play an important role. This study aims to investigate how students react differently to mobile device from a cognitive style perspective. The results suggest that students in the mobile device scenario had more engagement and performed better than those in the desktop computer scenario. Furthermore, Holists who made more movements and Serialists who frequently used the Keyword Search could achieve good performance in the desktop computer scenario. On the other hand, the students performed similarly in the mobile device scenario though Serialists who made more repeated visits and browsed more pages could have better performance.

Keywords: Cognitive styles, mobile device, technology-based learning tool

1. Introduction

The advancement of wireless communication technologies has recently provided an opportunity for educators to use new technology-based learning tools. Among various technology-based learning tools, mobile devices (MDs) are being widely applied to support student learning (Hein & Irvine, 1999). This is due to the fact that MDs offer ubiquitous information access (Zhang, 2007). More specifically, the MDs are portable so geographical access barriers can be overcome (Gulati, 2008). Thus, educational practice can be performed any places with MDs (Cavus, 2011).On the other hand, the screen size of a MD is small (Kukulska-Hulme, 2007). Accordingly, the MDs may not suit to everone. In particular, diversities exist among students, in terms of their knowledge, skills, and needs (Chen & Macredie, 2004). Therefore, there is a need to examine relationships between individual differences and the use of MDs.

Among a variety of individual differences, previous research found that cognitive styles greatly affect student learning (Chen & Liu, 2011) because it refers to a person's information processing habits, capturing an individual's preferred mode of perceiving, thinking, remembering, and problem solving (Messick, 1976). In this vein, the study reported in this paper aims to examine students' different reactions to the DCs and the MDs from a cognitive style perspective. To this end, two research questions are investigated: (a) how students react differently to the DCs and the MDs; (b) how cognitive styles affect their reactions to the DCs and the MDs. In order to obtain a complete understanding, both learning behavior and learning performance are applied to find answers for the abovementioned two research questions. Answers to these two questions are sought by using a data mining approach to analyze students' learning patterns because data mining has been successfully applied to examine students' learning behavior (Chen & Liu, 2008).

2. Methodology Design

44 students from a university took part in our empirical study. 21 students were assigned to a DC scenario, in which students interacted with the WBL system via a DC. On the other hand, 23 students were allocated to a MD scenario, in which students interacted with a Web-based learning (WBL) system via a MD, i.e., an iPad. Regardless of the DC scenario or MD scenario, the WBL system gave the lecture of "Interaction Design" and included eight sections. The system provided two kinds of navigation tools. One is Keyword Search, which allows students to locate specific information based on their particular needs. The other one is Hierarchical Map, which provides a global picture of the subject content. Their interactions with the WBL system were recorded in log files. Furthermore, all of the participants were initially required to take a SPQ, which is an 18-item inventory for categorizing students as Holists or Serialists (Ford, 1985). According to the results of the SPQ, there were 26 Holists and 18 Serialists and no intermediate students. Subsequently, all participants needed to take the pre-test to identify their preliminary understanding of the subject content. In the next stage, they were required to complete practical tasks by interacting with the WBL system. More specifically, they needed to complete the tasks by finding information from the WBL system. Finally, the participants were requested to take the post-test to evaluate their learning performance. Both of the post-test and pre-test included 20 multiple-choice questions.

Data analyses were conducted using traditional statistical and data mining techniques. The former was applied to determine whether there are differences between the DC scenario and the MD scenario. The latter was employed to produce clusters of students that shared similar learning behavior, and subsequently the corresponding cognitive styles and learning performance for each cluster were identified. Among various data mining techniques, K-means was used to create clusters for this study because our recent studies (e.g., Chen & Liu, 2011) found that K-means is a useful tool to cluster students' behavior.

3. Results and Discussions

3.1 Learning Behavior

After carefully examining students' learning behavior showed in their log files, we found that the hierarchical map was rarely used, regardless of the DC scenario (Mean = 8.73; SD = 16.46) or the MD scenario (Mean = 11.67; SD = 33.17). Thus, the frequencies of the use of the hierarchical map were excluded. In other words, only five attributes are considered as the inputs of the K-means algorithm: (1) the frequencies of using Keyword Search, (2) the frequencies of making movements, (3) the frequencies of repeated visits, (4) the number of pages browsed, and (5) the time spent for completing the tasks. As showed in Tables 1 and 2, students used fewer keywords ($t=5.129$; $p<.01$), made fewer movements ($t=3.031$; $p<.05$), had fewer repeated visits ($t=4.962$; $p<.05$), browse fewer pages ($t=4.987$; $p<.001$) and spent less time for completing the tasks ($t=3.987$; $p<.05$) in the DC scenario than those in the MD scenario. These findings imply that students in the former had more engagements than those in the latter.

3.1.1 The Desktop Computer Scenario

As showed in Table 1, students' learning behavior in the DC scenario are grouped based on the following trends:

- **C 1:** Students had the lowest frequencies of using the Keyword Search, made the fewest movements, made the fewest repeated visits and browsed the fewest pages.
- **C 2:** Students spent the least task time among the three clusters. However, they made the most movements, the most repeated visits and browsed the most pages.
- **C 3:** Students spent the most task time and had the highest frequencies of using the Keyword Search.

After checking the corresponding cognitive style for each cluster, we found that the distribution of Holists and Serialists in each cluster is similar. In other words, cognitive styles did not affect students' learning behavior in the DC scenario. A possible reason is that DCs have been the mainstay of the computing world for more than 20 years (Masters & Ellaway, 2008). Nowadays, most students are familiar with DCs so cognitive styles have no effects on students' learning behavior in the DC scenario.

Table 1. The mean and standard deviation of each attribute in the DC scenario

Attributes		Overall	C 1	C 2	C 3
Task Time	Mean	2974.52	2918	2844.71	3258
	SD	546.79	616.28	420.67	576.82
Keyword Search	Mean	34.52	18.89	44	49.4
	SD	20.13	9.12	22.44	10.97
Movement Made	Mean	95	27.67	174.71	104.6
	SD	68.75	7.23	32.63	22.24
Repeated Visits	Mean	19.38	5	35	23.4
	SD	14.96	2.35	9.73	7.37
Pages Browsed	Mean	75.62	22.67	139.71	81.2
	SD	54.34	5.22	25.06	15.19

3.1.2 The Mobile Device Scenario

As showed in Table 2, the trends of students' learning behavior in the MD scenario are:

- **C1:** Students spent the least task time and had the lowest frequencies of using the Keyword Search of the three clusters. Moreover, they made the fewest movements, made the fewest repeated visits and browsed the fewest pages.
- **C2:** Students had the highest frequencies of using the Keyword Search, regardless of the DC scenario or MD scenario.
- **C3:** Students spent the most task time, made the most movements, made the most repeated visits and browsed the most pages among the three clusters.

Cluster 2 (N=9, 39%) and Cluster 3 (N=9, 39%) are the two major clusters in the MD scenario. After identifying the corresponding cognitive style of each cluster, we found that most Holists (N =6, 42.86%) appeared in Cluster 3. As mentioned earlier, students in Cluster 3 made the most movements. These findings reveal that Holists tended to make a lot of movements. This may be due to the fact that Holists prefer to get an overview so they tend to get a global picture by making many movements. Conversely, most Serialists (N =5, 55.56%) emerged in Cluster 2, where they frequently used the Keyword Search. A possible reason is that Serialists tends to focus on procedural details when processing information in a learning context. On the other hand, the Keyword Search, which can facilitate students to locate specific information, is useful for Serialists to get particular details (Pask, 1976).

Table 2. The mean and standard deviation of each attribute in the MD scenario

Attributes		Overall	C 1	C 2	C 3
Task Time	Mean	3606.83	2564	3799.33	3993.67
	SD	733.88	366.4	647.38	324.27
Keyword Search	Mean	44.74	34.2	51.44	43.89
	SD	12.11	12.62	6.56	12.64
Movement Made	Mean	176.91	131.4	166.78	212.33
	SD	39.55	8.59	18.57	33.15
Repeated Visits	Mean	35.43	25.8	33.33	42.89
	SD	8.9	3.77	5.7	7.27
Pages Browsed	Mean	141.48	105.6	133.44	169.44
	SD	32.26	8.08	14.89	29.16

3.2 Learning Performance

In general, we found that students in the MD scenario (Mean = 14.5 SD=1.2) performed better than those in the DC scenario (Mean = 10.1 SD=0.7). As mentioned in Section 3.1, students with the MDs had more engagements than those with the DCs. These findings suggest that students can benefit from such engagements to get better performance. Furthermore, we also examined how different cognitive style groups performed differently in the DC and MD scenarios. Regarding the DC scenario (Figure 1), students in Cluster 3 got the highest gain score (Mean = 11.6; SD= 2.88) while those in Cluster 1 got the lowest gain score (Mean = 9.67; SD= 3.61). As described in Table 1, students in Cluster 3 most frequently used the Keyword Search while those in Cluster 1 least frequently used the Keyword Search. These findings suggest that frequently using the Keyword Search can help students explore a variety of concepts so that they achieve good performance. Moreover, we also found that Holists got higher gain scores than Serailsts in each cluster (Figure 1). In other words, Holists performed better than Serailsts in the DC scenario.

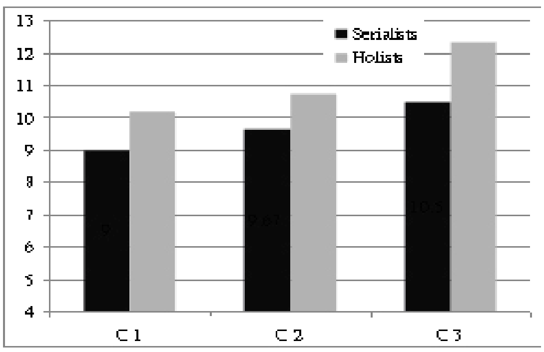

Figure 1. The performance of DC scenario

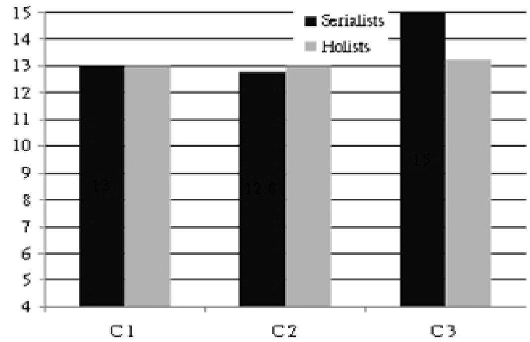

Figure 2. The performance of MD scenario

Regarding the MD scenario (Figure 2), students in each cluster got similar gain scores in the MD scenario. Thus, students' learning behavior is not associated with their learning performance in MD scenario. We, however, found that Serialists in Cluster 3 got the highest gain score. As mentioned earlier, student in Cluster 3 made the most repeated visits and browsed the most pages. These results reveal that making more repeated visits and browsing more pages can support Serialists to obtain better learning performance in the MD scenario. Unlike Serialists, Holists demonstrated similar performance in each cluster. In other words, Holists' learning behavior does not affect their learning performance.

4. Conclusions

Two research questions are examined in this study. The answer to the first research question is that students in the MD scenario had more engagement and performed better than those in the DC scenario. The answer to the second research question is that Holists who made more movements and Serialists who frequently used the Keyword Search could achieve good performance in the DC scenario. On the other hand, the students performed similarly in the MD scenario though Serialists who made more repeated visits and browsed more pages had better performance. The present study shows fruitful results but there are several limitations. Firstly, this study was only a small-scale sample. Further research needs to be undertaken with a larger sample to provide additional evidence. Another limitation of this study is that only cognitive styles were investigated. Thus, it is necessary to consider other human factors, such as gender difference and prior knowledge, in the future. Such evidence can not only be helpful to promote the use of MDs, but also is useful to incorporate personalization into ubiquitous learning environments.

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