Measuring simultaneous sources of Cognitive Load within a mobile learner

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Introduction

Mobile learning is a cognitively demanding activity and more frequently the ubiquitous nature of mobile computing means that mobile devices are used in cognitively demanding environments. Deegan and Rothwell (2010a) identified issues surrounding cognitive load as critical to mobile learning and mobile usability. Later, Deegan and Rothwell, (2010b), presented a model of sources of Extraneous Cognitive load that a mobile learner will experience (Figure 1).

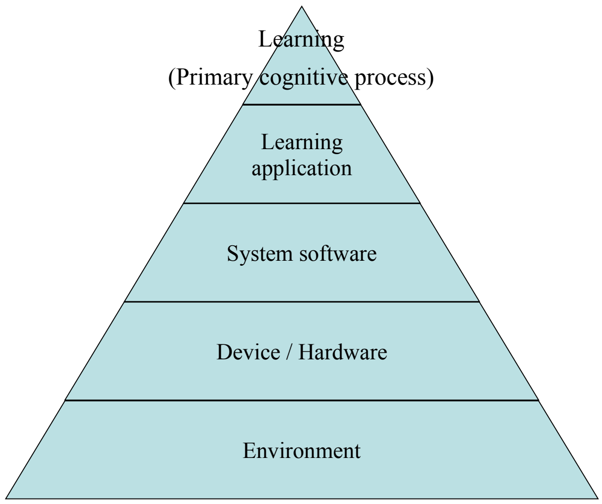

Figure *1* Sources of Cognitive Load

This research examines the nature of this use of mobile devices from a Learning, Usability and Cognitive Load Theory perspective. Two experiments are presented that seek to measure several sources of cognitive load inflicted on a learner simultaneously.

Method

Experiment 1 required each participant (n=82) to complete 10 mathematical problems whilst completing a memory based distraction. Participants were divided into two groups. Group 'a' experienced a simple distraction while group 'b' experienced a difficult distraction. A nine point likert scale was used to measure mental effort (Paas, 1992). Accuracy and mental effort of both the primary mathematical task and secondary distraction were measured and analysed with a one way MANOVA.

Experiment 2 was identical to experiment 1 except that the fifth mathematical task was replaced with a puzzle. This caused the participants (n=85) to pause while they dealt with a second distraction, in addition to the first memory based distraction. Accuracy and mental effort of the primary mathematical task, distraction and secondary distraction were measured and analysed with a one way MANOVA.

Results

Experiment 1 showed that several sources of Cognitive Load could be simultaneously and accurately measured. The participants could accurately rate the mental effort increase associated with the more difficult distraction while maintaining the same rating for the mathematical task. However, the performance of the mathematical task was affected by the distraction. Considering that the participants in each group rated the mental effort needed for the mathematical task similarly, despite having a poor performance when the distraction was more difficult, it seems likely that this change was subconscious. These finding echoes earlier work in which Deegan and Rothwell (2011) found that the link between performance and perceived cognitive load is not always correlated.

Experiment 2 showed, as expected, the change in the mental effort associated with the distraction was accurately rated by the participants; however, the participants also rated the primary task as more difficult, when in reality it had not changed. This implies that the second distraction affected the perceived mental effort associated with the primary task. This association was more pronounced when more cognitive load (primary distraction) was inflicted on the participant. Interestingly however, the high distraction did not have a significant effect on performance of the mathematical task, presumably because the second distraction (puzzle) affected both groups.

Discussion

These experiments demonstrate scenarios where cognitive loads, traditionally thought of as Extraneous Cognitive Loads, (Sweller *et al.* 2011), interact with sometimes unusual or unpredicted outcomes. However, it appears that these cognitive loads can, in fact, be measured by the user. This leads to two questions:

1) Are these loads actually extraneous?
2) Can several sources of cognitive load occur simultaneously with separate learning outcomes?

The results from this experiment has led to similar results being obtained (Deegan, 2013a, 2013b, 2013c) in which mental effort associated with the interface type (desktop or mobile) was obtained in addition to the primary task and distraction. These results further demonstrate that Cognitive Load Theory can be applied in more diverse environments than perhaps previously considered and that these can also generally inform Cognitive Load Theory itself. Specifically Human Computer Interaction can benefit from adopting certain aspects of Cognitive Load Theory. Ultimately, however, this research could lead towards the development of cognitive load aware applications to make cognitively demanding applications more usable.

References

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