Managing distractions in complex settings

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ABSTRACT
Mobile devices are being used in more and more complex settings such as cars or medical environments and these environments are causing serious distractions for the mobile user. This paper presents novel research that investigates mobile user experiences when interacting with cognitively demanding distractions. This research finds that, surprisingly, the user's primary task is not always affected by the distraction but, in this case, the actual interaction between user and device is. This observation initially appears to contradict current research which suggests that a distraction will affect the primary task. The main conclusion of this paper is that a user, when dealing with distraction, can balance their cognitive processes by applying less cognitive resources to the mobile device interaction in order to maintain their performance at the primary task. Essentially, the interface can appear more difficult and less user friendly.

Author Keywords
Mobile Usability; Mobile HCI; Cognitive Load Theory; Mobile learning; Cognitive Science.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Human Factors; Design; Measurement.

INTRODUCTION

Mobile devices are challenging usability professionals in many new and unexpected ways. Many of these challenges can be seen to stem from mobile device use in complex settings such as cars [21, 22] or medical environments [23, 24] etc. Mobile device use, in these settings, is difficult to identify and separate from the surrounding tasks and activities due to the notion of "interactional adaptation" as discussed in [21]. Some of these challenges have been investigated and it was discovered that one of the main issues facing the usability of these types of applications is cognitive load [1]. Cognitive Load Theory explains how the human mind interacts with instructional materials for learning and has several guidelines that are used to assist in the design of instructional material used for learning [2]. This paper will present the results of an experiment that investigates the cognitive effect of distractions on users. The experiment takes small first steps towards software that can predict changes to the user's cognitive load, inflicted by complex settings, and adapt its software to reflect these changes. 118 participants were recruited for this empirical experiment which is explained in detail below.

LITERATURE REVIEW

HCI is the study of how people interact with technology. HCI encompasses elements from disciplines such as computer science, engineering, psychology, philosophy etc. Usability can be viewed as a subset of HCI and deals more with the actual "use" of an artifact rather than other less tangible HCI aspects such as culture, society or behavior etc. Usability is defined by the ISO as "*the effectiveness, efficiency and satisfaction with which specified users can achieve specified goals in particular environments.*" [4]. A usable system should be easy to use and easy to learn [3]. In recent years a popular approach to Usability has been to make things 'easier' for the user. This approach stemmed, in part, from work done by Miller [5] which determined that working memory is limited. Cognitive Load theory acknowledges that working memory is limited but suggests ways to circumvent these limitations [2]. Cognitive Load is the demand for mental resources associated with processing information in working memory. Some researchers [2, 6-9] argue that our Cognitive Load can and will vary depending on the characteristics of the task and those of the user, a situation made all the more difficult when interactional adaption with the environment occurs. Cognitive Load Theory was originally created to help understand problem solving [6, 8, 10] but the theory itself can be used to apply to other scenario's such as mobile device use in complex environments. Deegan and Rothwell found that there were many extraneous distractions that a mobile user could face and presented a model of these distractions [12, p71]. By combining several methods of balancing Cognitive Load [2, 13-15] content designers can ensure that the user's cognitive load is at the suitable level with regard to the content. Usability professionals can make efforts to reduce likely sources of cognitive load with regard to the application interface, system software and device/hardware. Software developers are therefore left to attempt to control distractions caused by the environment by creating context aware software that will use the mobile devices inbuilt sensors to detect these distractions and adjust the content to suit. These three levels of 'content', 'usability' and 'context aware' are required to capture all the sources of extraneous distractions identified in Deegan and Rothwell's model.

EXPERIMENT

Three hypotheses were developed, H1: Cognitively demanding distractions affect the primary task, H2: Cognitively demanding distractions affect the usability of the interface and H3: Any observed differences will be more pronounced on a mobile device. The experiment is explained in detail as follows.

Method

Participants

118 participants were recruited from the online site Mechanical Turk[1]. Several recent studies have found Mechanical Turk to be a valid source of participant recruitment for behavioral and user studies [cf. 16-19]. In fact, Buhrmester *et al*. [17] and Ipeirotis [20] suggest that the representative demographic characteristics of Mechanical Turk may be at least as diverse as, and more representative, than traditional college or online based recruitments. Each participant was paid approximately $0.15 to complete the experiment which took 5 minutes.

Materials

Participants were expected to have their own computer, mobile device and access to broadband / the internet. The participants were randomly assigned to either the desktop group (n=56) or mobile phone group (n=62). The desktop group was given a link to the software and this would only work with a traditional desktop or laptop computer (e.g. windows operating system). The mobile group was given a different link to the software and this would only work with a mobile device (e.g. both device manufacturer and operating system were verified). The following mobile devices were used: Android (25), iPhone (19), Symbian (14), Windows (3), iPod (1). The learning task was a series of 10 mathematical problems in which the participant needed to add or subtract three "two" digit number similar to those used in [25]. The answer would always be two digits and fall between 25 and 90. Cognitive load was measured using a 9 point likert scale developed by Paas [11]. This scale is widely accepted as being an accurate measure of cognitive load [2].

Distraction

This experiment was designed to determine how different difficulty distractions affect the user's cognitive resources. Therefore, the distraction needed to be concurrent with the users tasks (e.g. the interaction and the task). For that reason a memory based distraction was chosen. A memory based distraction is, by nature, a concurrent distraction. Similar studies [25] have investigated performance of similar maths tasks and determined that levels of associated anxiety affected the task performance. A difficult and "overloading" memory based distraction was intended to cause the participants anxiety and affect the primary task. As stated concurrent tasks and distractions were deemed important, but what was the distraction or task was not critical at this stage. For example, a mobile phone may distract a person driving, but perhaps also the action of driving is distracting the person using the mobile phone (setting aside issues of legality!). Likewise perhaps the conversation from the passenger may distract both the mobile device use and the driving. In this regard the distraction used could be considered overly difficult. Both the task and distraction, used for the experiment, are only abstract constructs designed to suggest real life scenarios. Future experiments will use real world examples of distractions and base the experiment on more realistic tasks.

Procedure

Two levels of the distraction were applied to both groups. The levels were easy (low cognitive load) and hard (high cognitive load). The distraction required the learners to remember how many apples are displayed at the top of various pages throughout the primary task of completing the mathematical calculations. The low cognitive load distraction was to remember seven apples and the high cognitive load distraction was to remember seventy apples.

Results

Difficulty and interface type were the independent variables with two levels each, respectively. The dependent variables were task1, task2 and interface effort rating, task1and task2 performance, and time. The data was normally distributed and assumptions of variance-covariance were met. As such a two way MANOVA was used to analyze the data. Using Pillai's trace, there was no combined effect of difficulty and interface type on accuracy of task1 or task2, or the mental effort ratings of task1, task2 or the interface, $V=0.03$, $F(6,109)=0.595$, $p=0.73$, $\eta 2$ (partial eta squared)=0.03, observed power of 0.22. However, the MANOVA for difficulty alone, $V=0.29$, $F(6,109)=5.68$, $p=0.001$, $\eta 2 = 0.29$ showed that the difficulty of the distraction had a significant effect on the dependent variables with an observed power of 1. Also the MANOVA for the interface type alone $V=0.12$, $F(6,109)=2.47$, $p=0.03$, $\eta 2 =0.12$ showed that the interface type did have a significant effect on the dependent variables, with an observed power of 0.60. Follow up univariate analysis showed that difficulty of the distraction did not have a significant difference on the task1 performance or the task1 rating of cognitive load. The difficulty of the distraction did, however, have a significant effect on the task2 performance ($F(1,114)=8.38$, $p=0.005$, $\eta 2 =0.07$, observed power of 0.82), and the task2 cognitive load rating ($F(1,114)=18.22$, $p=0.00$, $\eta 2 =0.14$, observed power of 0.99) between the easy and hard group. The difficulty of the distraction also had a significant effect on the time that it took to complete the experiment ($F(1,114)=11.17$, $p=0.001$, $\eta 2 =0.09$, observed power of 0.91). Surprisingly the difficulty of the distraction also had a significant effect on the interface rating ($F(1,114)=11.17$,

1 http://www.mturk.com/

$p=0.001$, $\eta2 = 0.09$, observed power of 0.91), between the easy group and hard group. Further follow up univariate analysis showed that interface used did not have a significant difference on the task1 or task2 performances or the task1, task2 or interface ratings of cognitive load. However, a statistically significant difference between the time taken to complete the experiment ($F(1,114)=5.7$, $p=0.02$, $\eta2 = 0.05$, observed power of 0.67) was detected.

Discussion

Obviously when a distracting task is made difficult, it is likely that the associated performance and cognitive load associated with that task increases. What is unusual, however, and possibly not often reported, is the associated impact on simultaneous cognitive processes, such as the cognitive resources given to using the interface. If the performance of the task has not changed due to a distraction it is easy to suggest that the distraction did not have any effect. However, when one looks at several concurrent cognitive processes (such as cognitive processes associated with using the interface as well as the task) one might find that the distraction had an effect in other ways e.g. on the interface.

H1 was rejected in this instance: A cognitively demanding distraction was not found to affect the primary mathematical task performance or related rating of cognitive load. This in itself is unusual as current research suggests that a high secondary cognitive load can affect the primary performance [2, p78]. The simplest reason for this would be that the difficulty of the distraction was not cognitively demanding enough to cause a change in performance of the primary task. Future experiments should increase the difficulty of the distraction to see if this will affect performance.

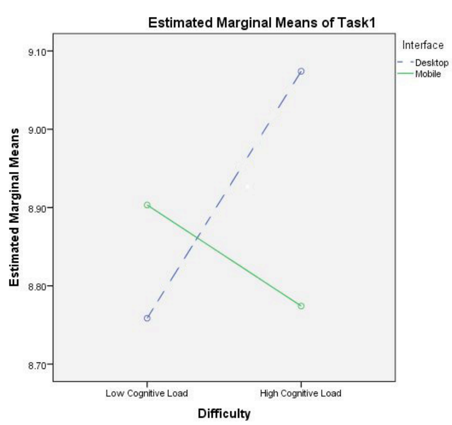

Figure 2. Task 1 performance

Figure 2 (above) shows the means obtained from the experiment for task1 performance. This graph demonstrates that while a significant difference was not observed there is an unusual occurrence. The desktop user's performance appears to increase with the more cognitively demanding distraction, while the mobile group's performance appears to diminish. Figure 3 (below) shows another interesting observation. The task1 cognitive load ratings for the mobile group seem more effected (although not significantly) by the high cognitive load distraction than the desktop users.

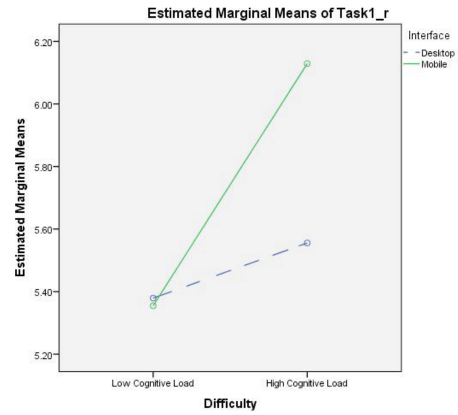

Figure 3. Task1 cognitive load rating (Task1_r)

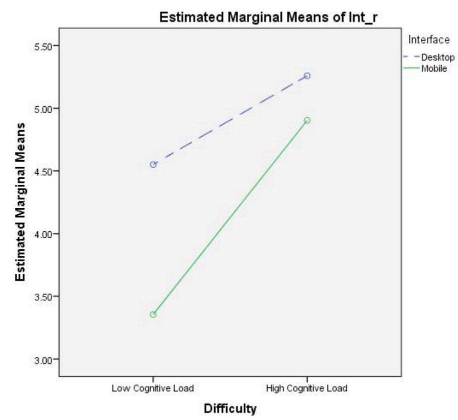

Figure 4. Interface cognitive load rating (Int_r)

H2 was accepted: Cognitive demanding distractions were found to affect the usability of the interface. Both mobile and desktop users felt that a cognitively demanding distraction affected the cognitive load associated with using the application interface. Interestingly, the participants felt that the interface was less demanding when used on a mobile device (figure 4 above).

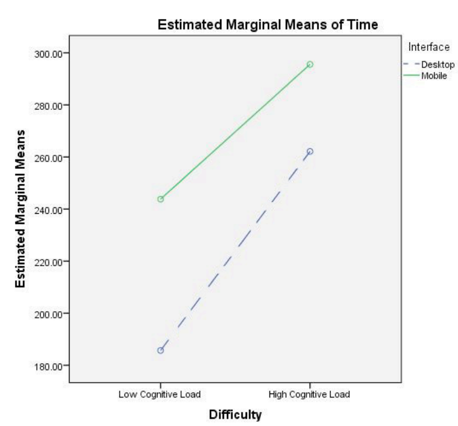

Figure 5. Estimated marginal means of time

When a more demanding distraction was introduced the mobile users experienced a sharper rise in cognitive load than the desktop users. H3 was also accepted: Statistically significant results were obtained when the time taken to complete the experiment was compared between desktop and mobile groups (Figure 5, above, measured in seconds). This suggests that mobile users took longer than desktop users. However, these findings have two main flaws. The first is that the distraction can be as cognitively demanding as the actual task. This serves to reiterate an earlier point that sometimes what can be a primary task in a given context and can become a distraction in another. The second flaw is a lack of ecological validity, specifically, the experiment is not really an accurate representation of real world problems or scenarios (e.g. the distraction will most likely be in the environment, not within the mobile device). This was necessary to isolate and measure the various cognitive loads. Future experiments will use more naturally occurring complex settings, tasks and distractions to address these flaws.

CONCLUSION

This research demonstrates the need for HCI to consider the concurrent cognitive processes that a mobile user is engaged in, when using a mobile device. Cognitive Load Theory can help inform Mobile HCI to better understand this need. This research shows that distractions, that affect mental resources, can also affect the resources that have been allocated to using a mobile device in unpredicted ways. Specifically it appears that the cognitive resources dedicated to the device interaction can suffer before the actual task performance will suffer, as predicted by Sweller *et al.* [2]. This seems to be an example of cognitive balancing and demonstrates that the user may subconsciously balance cognitive load at the expense of the interaction in an effort to maintain the performance of the primary task. Future work should increase the cognitive load inflicted by the distraction to see how this increased cognitive load will further affect the primary task and the interaction between the user and mobile device.

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