2007

The Impact of Distractions on the Usability and the Adoption of Mobile Devices for Wireless Data Services

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THE IMPACT OF DISTRACTIONS ON THE USABILITY AND THE ADOPTION OF MOBILE DEVICES FOR WIRELESS DATA SERVICES

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Abstract

Mobile devices are becoming increasingly popular, having already reached over 1.5 billion mobile subscribers. Although progress has been made in terms of technological innovations, usability challenges still face m-Business (mobile business) application. This paper explores how the context of use impacts the usability of mobile devices. An empirical study was undertaken to investigate the impact of distractions on the usability and its subsequent effect on consumers' behavioural intention towards using a Personal Digital Assistant (PDA) for wireless data services. Distractions were simulated in this study in the form of either user motion or environmental noise (i.e. background auditory and visual stimuli). A structural equation modelling analysis confirmed the impacts of distractions on perceived usability (i.e. efficiency and effectiveness) of, and in turn the users' satisfaction with and behavioural intention to use, a PDA for wireless data services. Implications of these findings for theory, practice, and future research are outlined.

Keywords : Usability, distraction, adoption, mobile.

1 INTRODUCTION

Mobile devices are becoming increasingly popular, having already reached over 1.5 billion mobile subscribers worldwide (OneUpWeb 2005). Also known as handhelds these devices come in various form factors with mobile phones and personal digital assistants (PDAs) being most prominent. As consumers' technology fears and adoption costs are reduced, mobile devices have become "mainstream" around the developed world. Such devices propose increasing value to consumers found in "anytime / anywhere" connectivity, communication, and data services. Progress has been made in terms of technological innovations, yet many mobile applications remain difficult to use, lack flexibility and robustness.

Key usability challenges facing m-Business (mobile business) applications include technology issues relating to mobile device interface attributes such as limited screen size, limited input methods, and navigation difficulties. Additionally, the mobile user has to share his or her attention between the task (application) and the surrounding environment. Furthermore, the individual characteristics (e.g. age, culture) may be key factors in their ability and preferences to use a mobile device. Thus, the context of use, incorporating the above factors, may have a significant impact on the usability of such devices.

The concept of *context of use* as it relates to usability emerged out of the work of several researchers (e.g. Bevan and Macleod 1994; Lee and Benbasat 2003; Tarasewich 2003; Hassanein and Head 2003), who suggested many variables beyond the immediate interface may impact usability. Although the definition of *context* may be slightly varied, the takeaway is that usability experiments need to consider various contextual factors. In particular when assessing the usability of mobile devices and services, the following factors should be considered (adapted from Hassanein and Head 2003):

- User (e.g. prior relevant/computing experience, age, education, culture, motion)
- Environment (e.g. lighting, noise – music, speech, white noise)
- Task (e.g. complexity, interactivity)
- Technology (e.g. interface design – input/output modes, size, weight, actual device vs. emulator)

The results of such contextual usability studies should guide the design of mobile devices and services resulting in better user satisfaction and consequently higher rates of adoption for such devices and services.

This paper explores the impact of context on the usability of mobile devices. Specifically, the paper empirically investigates the impact of distractions on the usability and its subsequent effect on consumers' behavioural intention to use PDAs for wireless data services. Distractions are ever present during real-world use of mobile devices but the nature and extent to which user performance is affected by their presence is unknown. This study will contribute to theory by extending cognition related theory to usability. It will also contribute to practice by providing a better understanding of contextual usability factors that have negatively influenced consumer adoption of wireless data services.

2 THEORETICAL DEVELOPMENT AND RESEARCH MODEL

2.1 Usability Dimensions

Several approaches to measuring usability have been put forth by scholars. One of these approaches was proposed by Nielsen (1993), where usability was measured as the learnability, efficiency, memorability, less errors, and satisfaction involved in a user's interaction with a technology. Rubin (1994) proposed similar usability dimensions, including learnability, effectiveness, usefulness, and attitude. Quesenbery (2003) defined usability in terms of five dimensions: efficiency, effectiveness, engagement, error tolerance, and ease of learning. For this study usability is defined and measured according to the definition of usability set forth by the International Organization for Standardization (ISO-9241 1998), which includes the dimensions of:

- Efficiency: the level of resource consumed in performing tasks,
- Effectiveness: the ability of users to complete tasks using the technology, and the quality of output of those tasks,
- Satisfaction: users' subjective satisfaction with using the technology.

The ISO definition of usability was chosen for this study in part because it is the international standard of measuring usability. The use of this standard allows for consistency with other studies in the measurement of efficiency, effectiveness, and satisfaction (Brereton 2004). Also, a recent qualitative review of 45 empirical mobile usability studies identified these three constructs as core usability dimensions (Coursaris and Kim 2006). At least one of these three constructs was measured in each of the studies reviewed.

Further to this definition, Frokjaer et al. (2000) tested these three constructs of efficiency, effectiveness and satisfaction for correlation in reference to usability. The results show that the three constructs should be considered discriminant, unless domain specific studies suggest otherwise, and that all three should be included in usability testing. Watters (et al. 2003) further argued that efficiency and effectiveness can be grouped under the concept of performance, which in turn impacts user satisfaction. Oliver's (1980) work on product and/or service expectations gave rise to a prominent Marketing theory, namely Expectancy-Disconfirmation Theory (EDT). According to EDT, satisfaction with a product or service is directly affected by a consumer's post-trial perceptions regarding its performance. Bridging Frokjaer's work with that of Oliver's, it is argued that each discriminant performance dimension (i.e. efficiency and effectiveness) carries a respective satisfaction measure (i.e. satisfaction with efficiency and satisfaction with effectiveness). As the impact of performance on satisfaction will be tested in this study by focusing on mobile devices for wireless data services, the following hypotheses are postulated:

H2a: Higher levels of perceived efficiency of a mobile device will lead to higher levels of user satisfaction with the efficiency of the mobile device for wireless data services.

H2b: Higher levels of perceived effectiveness of a mobile device will lead to higher levels of user satisfaction with the effectiveness of the mobile device for wireless data services.

2.2 Usability and Distractions

Researchers need to pay close attention at the dyadic inverse relationship that exists between methodological rigour and relevance of findings (Lindroth et al. 2001). It can be argued that the more natural the experimental setting in a study is the more relevant and applicable the results will be. However, typically, usability studies are performed in controlled laboratory settings where external variables (e.g. distractions), are absent (Kallinen 2004) in an attempt to uphold a rigorous methodology. "Distractions" can be auditory, visual, or motion related. By omitting distractions, however, such studies exclude factors that would typically be present in a real-world setting and therefore the external validity of their findings is limited. This limitation arises mainly from the observation that distractions negatively affects information processing and performance (Baker and Holding 1993). Both short-term memory (also known as working memory) and attention span are subject to cognitive constraints (Baddeley 1986). Nicholson et al. (2005) describe cognitive load as "the total amount of mental activity imposed on the working memory at an instance in time." Any single distraction adds to the total cognitive stimuli (i.e. load) thereby reducing information processing efficiency and effectiveness and, by extension, performance.

Extensive literature focuses on auditory and visual distractions and their impact on performance. A quiet environment has been shown to result in higher efficiency, while the presence of irrelevant sound lowers mental efficiency and performance due to the obligatory cognitive process of organizing unattended information (Hughes and Jones 2003). It is interesting to note that both noise and music hinder performance (Stansfeld et al. 2000; Persson Waye et al. 2001), but music has been shown to have a more substantial negative impact on performance compared to noise (Umemura 1992). Additionally, increased variability of background noise results in lower performance (Hughes and Jones 2001).

Visual distractions may elicit different responses from the brain than auditory distractions, but its impact on performance is also negative. In fact, it may be more difficult to return to ones thoughts and task after certain visual distractions than after an auditory distraction (Berti and Schronger 2001).

Motion can also be a source of distraction. Ljungberg's et al. (2004) study supports the argument that the combination of a subject's motion (e.g. walking) with the presence of any other auditory or visual distraction would impact the subject's performance negatively, as they would have an additive effect on cognitive load. Other studies have also shown the negative effect of various forms of distractions on performance (Baker and Holding 1993). Thus, it can be inferred that the greater the level of distraction (auditory, visual or motion related) the more adverse its impact will be on performance. Hence, the following hypotheses are proposed:

H1a: Exposing users to higher levels of distractions will negatively influence their perceived efficiency of a mobile device for wireless data services.

H1b: Exposing users to higher levels of distractions will negatively influence their perceived effectiveness of a mobile device for wireless data services.

2.3 Usability and Technology Adoption

As outlined above, usability can impact the growth of m-Business (i.e. poor usability hinders adoption). Here we examine the impact of usability on the adoption of mobile devices (in this study, PDAs) for wireless data services. According to the Theory of Reasoned Action (TRA) (Fishbein and Ajzen 1975), a consumer's "behaviour is determined by his/her behavioural intention, and behavioural intention is determined by both the person's attitude and subjective norm concerning the behaviour in question", in this case being the use of PDAs for wireless data services. Furthermore (in TRA), attitude is determined by the consumer's beliefs about consequences of performing the behaviour and the evaluation of those consequences. Usability is one such belief that may directly or indirectly impact a user's attitude towards using mobile devices (Hsu and Chiu 2004). Therefore it can be argued that usability impacts attitude, which in turn determines behavioural intention. Similar to TRA, the Technology Acceptance Model (TAM) (Davis et al. 1989) also argues that actual use of an information system (e.g. mobile device) is impacted by the user's behavioural intention to use the technology. As subsequent studies have shown there is a strong positive relationship between attitude towards use, behavioural intentions towards use, and actual use of a technology (Venkatesh 2000). Therefore, measuring consumer's behavioural intention towards using a mobile device for wireless data services may suffice in predicting actual usage of this technology.

A plethora of studies suggest a strong effect between satisfaction and a consumer's behavioural intention to use a product (e.g. Mittal et al. 1999; Taylor and Baker 1994). Several studies have validated the positive influence of higher levels of user satisfaction on intention to use and actual use of information systems (DeLone and McLean 1992; Seddon 1997; Rai et al. 2002). Hence, the following hypotheses are proposed linking the two dimensions of user satisfaction identified in subsection 2.1 above (i.e. satisfaction with efficiency and satisfaction with effectiveness) with a user's intention to use a mobile device for wireless data service:

H3a: Higher levels of user satisfaction with the efficiency of a mobile device will positively influence the user's intention to use it for wireless data services.

H3b: Higher levels of user satisfaction with the effectiveness of a mobile device will positively influence the user's intention to use it for wireless data services.

Our proposed research model and hypotheses are outlined in Figure 1 below.

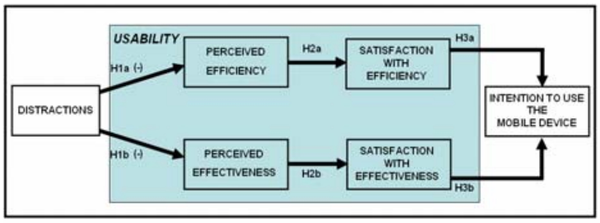


Figure 1. Proposed research model

3 METHODOLOGY

3.1 Experiment Design and Procedure

An empirical study was conducted to validate the proposed research model by testing our proposed hypotheses. The study was designed as a 2 x 2 factorial design (Factor 1: *User motion*; Factor 2: *Environment distractions* in the form of auditory and visual stimuli). This design allowed for any differences found among the four groups of subjects to be attributed to the increased levels of distraction as a result of user motion and/or both visual and auditory cues in the environment. This approach was used in previous usability studies by Watters (2003) and Chen and Vertegaal (2004), while a variant (2 x 3 factorial design) was employed by Kjeldskov and Stage (2004).

Experiment tasks involved the use of four PDA applications adapted from earlier studies: sending text messages (James and Reischel 2001), scheduling an appointment in the calendar and updating the address book (Lindroth et al. 2001), and searching the Web on a PDA (Rodden et al. 1993). The PDA selected, i.e. RIM's Blackberry 7250 with a QWERTY keyboard input, is a fair representative of typical PDAs currently available in the market in terms of the supported functionality and general form factor. The four tasks selected create the most value for consumers, second only behind voice communication (Jarvenpaa et al. 2004). All tasks were randomized within- and between-applications.

A total of 93 participants were recruited for the study, with a minimum of 20 subjects in each of the four treatments. This sample was well above the required total sample size of 40 for the Partial Least Squares analysis methodology employed in this study (Chin 1998). Each subject participated in only one treatment group, and assignment of subjects to groups was fully randomized to control for confounding effects due to differences in subject characteristics. Every participant received $10 for their participation that lasted 45 minutes. Participants progressed through the following experiment procedure: pre-test survey, instructions, training, controlled lab experiment, and post-test survey. Participants were not allowed to interact with others during the experiment in an attempt to isolate the conditions that were being tested and to increase the realism of the task.

Similar to Chen and Vertegaal (2004) and Nicholson et al. (2005), the four groups of subjects conducted the experiment under varying cognitive loads. The tasks completed were the same in all experimental treatments, with only user motion and auditory/visual stimuli as the changing parameters. To study the effect of user motion on performance, subjects were asked to complete the tasks either being seated or while walking in a controlled environment (i.e. large room in a building), staying within the boundaries of an outlined path on the ground that is changing (i.e. non-linear), and walking at a steady pace. To study the effect of auditory and visual distractions on performance subjects were asked to undertake the tasks either in the absence or presence of background noise (in this study music and speech) and visual stimuli (in this study the presence of and motion by five actors hired for this study). Again, distractions in this study were either the isolated or combined effects of user motion and/or visual and auditory stimuli in the environment, which served as the manipulation of the exogenous construct of the research model.

3.2 Subjects

The 93 participants recruited for this study were native English speakers, approximately of equal gender distribution, and covering a broad range for age and education. Subjects were recruited from a major Canadian university and included students, staff, and faculty. This strategy was aimed at soliciting a convenience sample that in fact displayed representative mobile user characteristics in terms of the control variables (i.e. age, gender, education). Of the 93 participants recruited, 87 usable questionnaires were collected. This group exhibited an average age of 28, 97% were at least college-educated, and the women to men ratio was 60/40 – none of the participants had any prior experience with wireless data services. ANOVA tests found no significant differences for subjects in the various treatment groups in terms of subject characteristics (i.e. age, gender, education). Therefore, randomization of assignment across groups was successful in terms of the control variables.

3.3 Instrument Scales and Validity

The questionnaire used for data collection contains scales that measure the various constructs shown in the research model and are provided in Table 1. All scales were adapted from prior studies, which had established their reliability and validity, thereby satisfying content validity. In accordance with the advice of Fishbein and Ajzen (1975) and Davis (1989) all instrument items were adapted to the use of the mobile device rather than to general IS use. When the questionnaire was conducted items within the same construct group were randomized to prevent systemic response bias. Upon further testing it was shown that non-response, temporal, and common method biases were not present in our data set.

The factor loadings for the total set of items used in this study are summarized in Table 1. Hair et al. (1995) suggest that an item is significant if its factor loading is greater than 0.5 to ensure construct validity. Adherence to this criterion required the modification of only one scale (Distraction, measured by the TLX scale) through the removal of two items: TLX5 and TLX6. TLX, or Task Load Index, was initially used by Hart and Staveland (1988) to capture study participants' cognitive load. After the removal of the non-valid items, each item was re-validated by testing its item-to-total correlation measure, where all items had higher measures than the 0.35 threshold suggested by Saxe and Weitz (1982).

Item	Question	Loading	Item-Total Correlations
TLX1	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy/simple/forgiving (i.e. LOW) or demanding/complex/exacting (i.e. HIGH)?	0.820	0.736
TLX2	How much physical activity was required (e.g. pushing, puling, turning, controlling, activating, etc.)? Was the task easy/slow/slack/restful (i.e. LOW) or demanding/brisk/strenuous/laborious (i.e. HIGH)?	0.662	0.526
TLX3	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow or leisurely (LOW) or rapid and frantic (i.e. HIGH)?	0.784	0.712
TLX4	How hard did you have to work (mentally and physically) to accomplish your level of performance? (LOW/HIGH)	0.860	0.824
TLX5*	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals? (GOOD/POOR)	-0.623	-0.279
TLX6*	How insecure, discouraged, irritated, stressed and annoyed (i.e. LOW) versus secure, gratified, content, relaxed and complacent (i.e. HIGH) did you feel during the task?	-0.360	-0.208
PerEffi1	Learning how to use the mobile device for wireless data services was easy.	0.686	0.553
PerEffi2	Using the mobile device for wireless data services was fast.	0.907	0.800
PerEffi3	The mobile devise was user friendly for wireless data services.	0.898	0.773
PerEffi4	Using the mobile device for wireless data services was easy.	0.768	0.619

SatEffi1	Thinking about my experience with the efficiency of this device for wireless data services, I feel … Terrible (1) ….. Delighted (7)	0.894	0.800
SatEffi2	Thinking about my experience with the efficiency of this device for wireless data services, I feel … Very displeased (1) …. Very pleased (7)	0.931	0.863
SatEffi3	Thinking about my experience with the efficiency of this device for wireless data services, I feel … Very dissatisfied (1) …. Very satisfied (7)	0.878	0.795
SatEffi4	Thinking about my experience with the efficiency of this device for wireless data services, I feel … Frustrated (1) …. Contented (7)	0.886	0.791
PerEffe	I was able to complete all wireless data services on the mobile device successfully.	1.000	N/A
SatEffe1	Thinking about my experience with the effectiveness of this device for wireless data services, I feel … Terrible (1) …. Delighted (7)	0.943	0.898
SatEffe2	Thinking about my experience with the effectiveness of this device for wireless data services, I feel … Very displeased (1) …. Very pleased (7)	0.959	0.922
SatEffe3	Thinking about my experience with the effectiveness of this device for wireless data services, I feel … Very dissatisfied (1) …. Very satisfied (7)	0.931	0.883
SatEffe4	Thinking about my experience with the effectiveness of this device for wireless data services, I feel … Frustrated (1) …. Contented (7)	0.925	0.862
BI1	Given that I had access to the mobile device, I predict that I would use wireless data services in the near future.	0.976	0.904
BI2	Assuming I had access to the mobile device, I intend to use wireless data services in the near future.	0.976	0.904

Note: * denotes items removed from the subsequent analysis
TLX – NASA Task Load Index, used to capture the participants' cognitive load (including distractions) (Hart and Staveland 1988) / PerEffi – Perceived Efficiency / SatEffi – Satisfaction with Efficiency / PerEffe – Perceived Effectiveness / SatEffe – Satisfaction with Effectiveness / BI – Behavioural Intention to Use

Table 1. Construct Items and their Factor Loadings

Results of tests for convergent validity (Bagozzi, 1981), discriminant validity (Bagozzi, 1981; Fornell and Larcker, 1981), construct means and Cronbach's alpha can be found in Table 2. All constructs had adequate reliability (Carmines and Zeller, 1979) and internal consistency well above the 0.7 threshold (Nunnally 1978). Cronbach α-values were satisfactory for our constructs (0.844 - 0.956) and constructs' AVE exceeded the 0.5 benchmark for convergent validity (Fornell and Larcker 1981). The square root of the variance shared between a construct and its items was greater than the correlations between the construct and any other construct in the model (see Table 3) suggesting discriminant validity (Fornell and Larker 1981). Discriminant validity was confirmed by verifying that all items load highly on their corresponding factors and load lowly on other factors (see Table 4).

	TLX	PerEffi	SatEffi	PerEffe	SatEffe	BI
Arithmetic Means (all items)	9.325	5.421	5.051	5.581	5.307	5.451
Arithmetic Means (used items)	8.082	5.421	5.051	5.581	5.307	5.451
Cronbach's α Reliability	0.852	0.844	0.919	N.A.	0.956	0.950
Internal Consistency	0.864	0.890	0.943	N.A.	0.968	0.976
Convergent Validity (AVE)	0.704	0.672	0.805	N.A.	0.883	0.952

Table2. Construct Statistics

	TLX	PerEffi	SatEffi	PerEffe	SatEffe	BI
TLX	**0.839**[6]					
PerEffi	-0.526[7]	**0.820**				
SatEffi	-0.503	0.721	**0.897**			
PerEffe	-0.275	0.414	0.373	**N.A.***		
SatEffe	-0.315	0.465	0.513	0.422	**0.940**	
BI	-0.154	0.226	0.178	0.226	0.561	**0.976**

Table 3. Correlation Matrix and Discriminant Validity Assessment

ITEM	TLX	PerEffi	SatEffi	PerEffe	SatEffe	BI
TLX1	**0.872**	-0.463	-0.411	-0.281	-0.289	-0.146

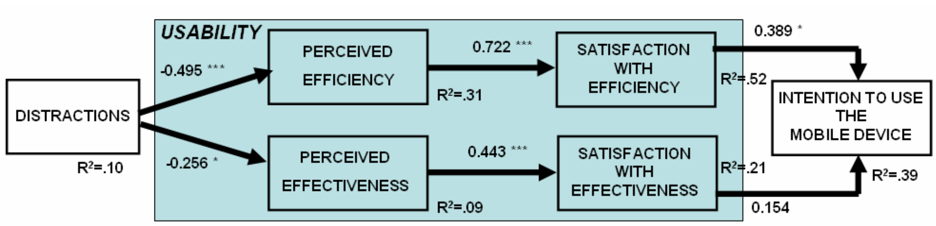
TLX2	**0.724**	-0.443	-0.396	-0.199	-0.212	-0.105
TLX3	**0.823**	-0.374	-0.394	-0.157	-0.253	-0.069
TLX4	**0.918**	-0.468	-0.471	-0.270	-0.291	-0.173
PerEffi1	-0.236	**0.681**	0.411	0.319	0.277	0.171
PerEffi2	-0.522	**0.907**	0.658	0.420	0.428	0.228
PerEffi3	-0.480	**0.901**	0.680	0.360	0.416	0.166
PerEffi4	-0.439	**0.769**	0.569	0.254	0.383	0.179
SatEffi1	-0.446	0.645	**0.893**	0.321	0.497	0.145
SatEffi2	-0.488	0.694	**0.930**	0.307	0.540	0.169
SatEffi3	-0.421	0.583	**0.878**	0.297	0.365	0.125
SatEffi4	-0.445	0.659	**0.886**	0.410	0.431	0.195
PerEffe	-0.275	0.414	0.373	**1.000**	0.422	0.226
SatEffe1	-0.413	0.653	0.732	0.424	**0.943**	0.237
SatEffe2	-0.453	0.682	0.800	0.403	**0.959**	0.259
SatEffe3	-0.510	0.664	0.815	0.397	**0.931**	0.195
SatEffe4	-0.504	0.726	0.827	0.454	**0.925**	0.254
BI1	-0.421	0.546	0.545	0.336	0.487	**0.976**
BI2	-0.452	0.554	0.566	0.312	0.528	**0.976**

Table 4. Matrix of Loadings and Cross-Loadings

4 RESULTS

The structural model shown in Figure 1 was tested using the variance-based Partial Least Square (PLS) method. The PLS model is shown in Figure 2. Overall, the model demonstrated high explanatory power. The R-square of the Behavioural Intention construct was 0.39, or 39% of the variance in user intentions to adopt mobile devices for wireless data services. It should be noted that the R-square value Perceived Effectiveness was relatively small (i.e. 0.09). This value does not necessarily pose a threat to the model's validity. Particularly in behavioural science research low R-square values are common and often the amount of actual association between constructs is higher than the variance accounted for by R-square (Cohen 1988). Low R-square values have also been reported in many technology adoption studies (e.g. Davis et al. 1989; Moon and Kim 2001). An additional explanation for this low R-square value may be that the Perceived Effectiveness construct was associated with only one construct (Distractions). Relative to multi-relationship models, these single or few-relationship associations often provide low R-square values (Nunnaly 1978). In the event that additional non-correlating constructs are introduced as antecedents to this construct with low R-square value (i.e. PerEffe), the score would probably increase considerably.

From the original six hypotheses, five were supported and one was not supported. Table 5 presents the validation of these hypotheses in more detail.



* significant at 0.05 level; ** significant at 0.01 level; *** significant at 0.001 level

Figure 2. The Proposed Structural Model

Hypotheses	From	To	Beta	t-Value	p-Value	Sig	Status

H1a	TLX	PerEffi	-0.495	4.519	< 0.001	***	Supported
H1b	TLX	PerEffe	-0.256	2.058	< 0.05	*	Supported
H2a	PerEffi	SatEffi	0.722	9.754	< 0.001	***	Supported
H2b	PerEffe	SatEffe	0.443	4.855	< 0.001	***	Supported
H3a	SatEffi	BI	0.389	2.175	< 0.05	*	Supported
H3b	SatEffe	BI	0.154	1.072	0.346		Not supported

Table 5. Hypotheses Validation for Structural Model

First, it was theorized that incremental cognitive load consequent of auditory/visual/motor distractions would negatively impact the users' performance on mobile devices for wireless data services. There was strong statistical support for the corresponding hypotheses, H1a and H1b, which referred to the direct negative effect of distractions on perceived efficiency and perceived effectiveness.

Second, on the topic of usability, both performance and satisfaction were decoupled into two respective components of Efficiency and Effectiveness. This decoupling obtained strong statistical support: H2a argued that higher levels of Perceived Efficiency influenced Satisfaction with Efficiency positively ($\beta = 0.722$; p-value < 0.001), and H2b argued higher levels of Perceived Effectiveness influenced Satisfaction with Effectiveness positively ($\beta = 0.443$; p-value < 0.001).

Lastly, adoption of mobile devices was explored by measuring the behavioural intention of users upon obtaining hands-on experience with wireless data services and their consequent level of satisfaction. From the two hypotheses proposed, only Satisfaction with Efficiency (H3a) was shown to be statistically significant in impacting the aforementioned behavioural intention; the path from Satisfaction with Effectiveness to Behavioural Intention (H3b) was not supported.

The control variables in this study (i.e. age, gender, education) were also analysed by running the model excluding them (uncontrolled), including them one at a time, and lastly including them all at the same time (controlled) in PLS. Any changes in R-square values may indicate an impact of an independent construct on dependents one(s) (Chin 1998). Overall, the fully controlled model improves the R-square values for all dependent constructs except for Satisfaction with Efficiency, which remained unchanged. Results showing moderate or considerable impacts include the following:

- Age had a considerable impact on Distractions (older subjects were more negatively impacted compared to younger ones);
- Gender had a considerable impact on Distractions and on Behavioural Intention (women were more impacted by distractions and had lower intentions to use wireless data services than men)

Additionally, the path coefficients and significance levels between the control variables and the dependent constructs were reviewed. A strong beta coefficient (0.237) and corresponding t-value (2.611) indicated that women may be affected more by distractions than men (p-value<0.01).

5 CONCLUSIONS

From a theoretical point of view, this work contributes to usability research by providing a better understanding of the impacts of auditory, visual and motion distractions on the use of mobile devices for wireless data services. We found that such distractions do have a significant negative impact on the perceived efficiency and effectiveness of mobile device use. While controlled laboratory studies help to ensure experimental rigor, academics must remember that usability may be greatly affected by context of use. This is particularly true for mobile devices, where distractions are more likely to occur while users are 'on the move'. Our experimental design attempted to approximate real-world scenarios for the tested product and services, while upholding a rigorous methodology, and can serve as an example for future empirical research on mobile usability

This study also examined the relative importance of efficiency and effectiveness in forming intentions of use for mobile devices and wireless data services. Previous work suggested that usefulness of products is more important than ease of use (Davis 1989). It appears that in the context of mobile devices for wireless data services, efficiency (a broader set of dimensions that encompasses ease of use) is the critical factor. On the contrary, effectiveness did not demonstrate a positive impact on use-intention formation.

For practice, this study's results have direct implications for designers and retailers of mobile devices. By decomposing satisfaction we offer relevant insight as to which performance dimension (i.e. efficiency) becomes critical in personal use decisions for a mobile device. Learnability, ease of use, and time required to complete a task are prevalent dimensions in the decision making process of using a mobile device for wireless data services, while successful task completion seems to be less relevant. Thus, complex interfaces that offer enhanced capabilities while having a toll on the efficiency of a mobile device may deter a consumer from using it. This observation is in agreement with the findings of Rust et al. (2006), who also call upon device developers to avoid "feature fatigue", i.e. overwhelming users by adding device functionality that leads to increased use complexity and product dissatisfaction. Such dissatisfaction often leads to product returns, customer attrition, and/or negative effects on brand equity. If repeat business (i.e. increasing the life-time value of the customer) is the goal, manufacturers are better off producing a device that is simple and easy to use than a "powerful" all-in-one device (Marcus 2003).

Additionally, strong beta coefficients and corresponding t-values indicate that women may be affected more by distractions than men, which is in agreement with the results of Bruni's (2004) work, who examined the impact of instant messaging on task performance. If women are less robust to distractions than men in the context of using a mobile device for wireless data services, it is likely that such applications (both professional and leisure) will not be as popular with women. Hence, manufacturers could arguably capture a market opportunity by designing different interfaces or offering special tools/accessories for mobile devices geared towards increasing usability for women. Similarly, usability and accessibility become imperative design considerations for devices aimed at older users, who were found to be more susceptible to distractions. Industry needs to pay closer attention to the significant strides being made in academia (e.g. Minimal Attention User Interfaces, Motor Input Assistance) communicated through scholarly journals and conferences.

Furthermore, the differences found in this study among user groups in terms of performance, satisfaction, and intention to use wireless data services highlight the importance of targeted marketing communications, thereby creating realistic product expectations for each user group. In addition, businesses providing decision aids, such as recommendation agents that help identify a user's real needs, may help increase the prominent importance of usability in the purchase decision (Rust et al. 2006). Furthermore, closing the gap between pre- and post-use consumer preferences may lead to product satisfaction, repeat business, and favourable effects on brand equity

As with all experimental studies, there are limitations that should be considered for this study which can prompt future research in this area. First, the study's tasks were simulated in a laboratory setting. Thus, any sense of urgency or other contextual responses that a user may experience in a real-setting may not arise here, other than those triggered by mobility, the visual and auditory environment. While this is a limitation in terms of the realism of the study, it is a means of controlling for additional variables that could not be otherwise measured during the experiment. Second, the experiment was carried out using one particular mobile device (RIM's Blackberry 7250) with one particular interface input mode (QWERTY keyboard). Results from this study should be validated across multiple mobile devices and interface input modes. Third, the experiment was conducted in a Canadian context and should not be generalized to other cultures before further validation.

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