A Disruptive Contexts Model for Mobile Commerce Systems

Mark A Hooper *mark.hooper@beds.ac.uk*
School of Computer Science and Technology
University of Bedfordshire
Luton, LU2 7EU, UK

Paul Sant *paul.sant@beds.ac.uk*
School of Computer Science and Technology
University of Bedfordshire
Luton, LU2 7EU, UK

Abstract

Mobile devices are becoming increasingly important within the on-line purchasing cycle. Thus the requirement for mobile commerce systems to become truly context-aware remains paramount if they are to be truly effective under different situations typical with mobility. This report investigates consumer physical and modal contexts and presents findings as to their relationships and potential influence upon m-commerce related behaviours. We show that through an understanding of the relationship between a user's affective state and level of purchase-decision involvement, a model of engagement can be produced. Through the introduction of the novel concept of disruptive contexts we show a significant effect upon these relationships and propose a system of engagement for the optimization of context-aware m-commerce recommender systems.

Keywords: M-Commerce, Purchase-Decision Involvement, Context-Awareness, Affective State.

1. INTRODUCTION

Research into improving the effectiveness of recommender systems has recognised the importance of context awareness [1]. However, m-commerce systems that utilise more abstracted environmental contexts such as perceptions of disruptive contexts including noise or distractions and their effect on user behaviour are relatively limited. It is now important to address this as we and technology become increasingly mobile within dynamic environments. Fortunately with the advance of smart-device sensor technology we are becoming well placed to define a new generation of mobile context-aware systems.

The focus of this paper is to demonstrate further understanding of how situational context influences an individual's cognitive behaviour. This is then used to produce a model of engagement that could be used to increase the yield of an m-commerce system by determining a user's levels of decision involvement with products as presented via a mobile device. To do this we investigate how elements of cognitive behaviour can change whilst using a mobile device in everyday activities. We posit that understanding user behaviour within context is critical in order to fully realise the potential for mobile recommender systems and m-commerce. We aim to do this by detailing an additional layer to the traditional recommender system model to determine the 'when' aspect of engaging with a user. This novel concept supports the process of effective placement of advertisements which should provide an edge to m-commerce marketing campaigns through the increase of user engagement.

Evidence is presented that mobile devices are used for product information search, review of alternatives and purchase activity, especially for high-involvement products [2]. These activities not only take place at home but also at retail locations, when travelling and simply when 'out and about' [2]. Product Involvement provides insight into how consumers engage with the advertisement process and is reliant on constructs that make up the ‘purchaser-product’ relationship, in particular personal preferences and perceptions, see summary by Kim [3]. Alongside this construct, Purchase-Decision Involvement, as defined by [4], is a concept used to capture the user’s mind-set towards an anticipated purchase, ideally measured as close as possible to planned marketing events. Knowledge of a user’s purchase-decision involvement ‘on the fly’ should be a valuable component to an m-commerce campaign.

As the mobile device user is subject to such varied situational contexts it is probable that these will affect both the user’s emotional [5] and decision making ability [6]. In order to advance m-commerce recommender system conversion rates, we explore this concept with the aim to further understand purchase-decision involvement within mobile user’s situational context. We explore the effect of different contexts and show that distraction, noise and activity all affect the relationship between user affective state and purchase-decision involvement. This supports the novel concept of disruptive contexts which can be used to help model a user’s potential engagement with product advertisements.

The rest of this paper is structured as follows. The following section discusses how disruptive contexts and user affective state can be used to determine levels of potential Purchase-Decision Involvement. We then present the methodology behind the implementation of our experiments using an android platform SiDISense (Situational Decision Involvement Sensing) developed for this purpose. Results of these experiments are then presented and analysed and then followed by a discussion. Finally a conclusion is presented alongside suggestions for further work.

2. USER DOMINANCE

This section focusses upon user dominance and why it is more important to the modelling of Affective State (mood, emotions etc.) for users of small, mobile devices than larger, static devices.

Affective computing involves computational methods for understanding user mood and emotions. There are many theories, each with a different focus which depends on specific attributes of a study’s requirements [7]. Dimensional theories are popular within the field of Computer Science because they are not overly reliant upon labels and they are implemented in either two or three dimensions providing a space within axis of specific states where affective state can be modelled. The three dimensional axis of Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness (PAD) [8] is a dominant dimensional model which has been shown as an effective method of modelling emotions and other affective states [9]. Examples where PAD has been successfully used in a mobile context include [10], [11] and [12].

The Pleasure and Arousal scales are most prevalent in research with some authors suggesting that the axis of dominance does not have a significant effect on behaviour [13] [14]. Positive emotions are also widely attributed as a control in user decision making within complex situations [15], [16]. Others have also suggested that dominance may be more relevant within the online retail context [17]. However other research findings have shown that dominance is as legitimate as pleasure and arousal scales and should not be ignored when considering consumer behaviour and retail marketing [18]. Broekens, [19], also advocates the importance of dominance in modelling or measuring user affect and suggests that aspects of dominance, e.g. power, control, approach vs. avoidance and coping potential, cannot be ignored.

So while the pleasure and arousal scales are well understood, dominance may have received less focus, especially within a mobile device context. Dominance, being the ability to act freely within a situation can be affected by change in settings and in turn increase the variety of behaviours we can display. Different online media formats have been shown to affect dominance which in turn can affect behaviours including impulse buying via its influence on the arousal channel [20]. Dominance’s influence over arousal is particularly important within a mobile context. Where arousal is described as either physical (active, energetic, alert or vigorous) or tense (anxious, jittery or nervous), dominance has been shown to have an effect, with a strong influence over tense arousal when the user is engaged in an online shopping environment [21].

Traits as described by Broekens [19], i.e. coping, control, power and influence, are more likely to be common in a mobile device user due to the variance in environment. So while a computer user will form a level of trust for the information presented to them [22], the mobile device user may need to form additional layers of trust due to their actual environment i.e. feel secure enough to complete a decision procedure. Finally, if a level of user dominance is involved then the traits are more likely to occur [19], which suggests that mobile device users will rely on additional dimensions of their affective state to engage in decision processes, e.g. arousal and dominance. With the above in mind we hypothesise that:

> *H1 – The Affective scale of Dominance (dominance-submissiveness) will be a reliable scale within a mobile context to determine aspects of cognitive behaviour*

The cognitive process, Purchase-Decision Involvement (PDI), is a particularly useful tool used to capture user anticipation mind-set towards a purchase especially when measured as close to the event as possible [4]. This suggests that the user PDI is subject to change, which could be due to personal preferences but also to changes in environment context or behaviour within that environment, e.g. if playing a sport, the user may not be inclined to engage in decision making. This effect will be particularly important for mobile device users. Purchase-Decision Involvement has also been shown to have a positive correlation with a user's affective state within a controlled environment [23]. While PDI and affective state relationships have not been used in a mobile context we suggest that PDI is a suitable tool against which to test hypothesis *H1*.

3. THE EFFECT OF DISRUPTIVE CONTEXTS

Previous works have presented a general consensus that positive mood favours heuristic processing through reduced capacity and that negative moods can facilitate the analysis of more complex data [24]. Physical contexts, however, could not only have an impact on the user's preferences [1] but also influence user Affective State relationships with the ability to process information [5] and decision control [6].

While a mobile device user may perform tasks in a preconditioned way, based upon general habits, other situational contexts, including time and place, should be considered independently [25]. A user may also associate different locations with different emotions [26], [27], or seek particular places to undertake tasks [2], however these are still choices selected via experience or habit. It is probable that other situational contexts of a particular location will collaborate to form different outcomes that influence the current mood and emotions and therefore behaviour in terms of ability in completing a task.

A user perception of dominance or 'control of situation' is related to judgements based on environmental stimuli and so determines their emotions and behaviours [21]. This suggests that decision processes may become more complex as situations become more physically challenging. The mobile user could be required to access additional layers of trust for both information presented by the device and the actual environment. They may also be potentially more influenced by traits, i.e. approach versus avoidance, coping, control, power and influence which in turn suggests that a level of user dominance is involved [19]. Therefore, as the mobile user is subject to more complex, disruptive and inconsistent environments they may access a more complex set of emotions than an average user in a controlled, familiar situation.

Physical environment and a user's perception of control has been shown to be important in mediating emotional and behavioural responses [6]. Physical stressors including noise and overcrowding can affect user behaviour and their evaluative ability [28]. Whereupon interruptions [29], noise [30], overcrowding [6] and physical activity [31] all have the potential to be disruptive and affect cognitive ability. Therefore a user is potentially less likely to engage with advertisement content in a disruptive environment within certain emotional contexts. Upon the understanding that user contexts of affective state and physical behaviour together with environment contexts can all contribute to cognitive capability and decision processes we can hypothesise:

H2 – That the influence of disruptive contexts on user cognitive processes can be demonstrated in a model of engagement for m-commerce systems

The above hypotheses will guide us in investigating the effect of disruptive contexts and Affective-Cognitive relationships. The following section presents the implementation of two experiments that are used to develop and test a context-aware model that relies upon user dominance and disruptive context with an aim to support existing m-commerce systems in determining when to place or recommend products.

4. METHOD

Online product advertisement placement is becoming ever more prevalent and we posit that context-aware m-commerce systems using methods that only focus on the relatively static contexts such as user's taste, online behaviours and demographics need to adapt to understand to a greater degree the impact of other elements of a user's situation. We explore physical contexts, including environment distractions and user activity, and their influence on user's ability to form purchase-decision involvement.

To test the hypotheses developed in previous sections we conducted an experiment that measured user's level of Purchase-Decision Involvement for a selection of products. This experiment was run twice to ascertain the accuracy of the model developed post first iteration. We favour 'in the wild' context with moods, emotions and environment that are not laboratory elicited but are authentic mobile device focussed situations. To conduct the experiments and corroborate our hypotheses we developed a user friendly, robust smart-phone Android application SiDISense (Situational Decision Involvement) that was used to manage several short questionnaires. The application is used to collect user input on a repeat basis which is then encrypted and uploaded to a remote server for analysis. Participants were invited to download the application to their own phone using Google's Play platform. The overall system workflow is as follows:

(i) System – notify user
(ii) Survey started by user or Survey resets if no engagement
(iii) User Interface – rate affective state
(iv) User Interface – rate situational/behaviour contexts
(v) User Interface – select products
(vi) User Interface – rate selected products for Product Involvement
(vii) User Interface – rate selected products for Purchase-Decision Involvement
(viii) System – encrypt and upload to server

As we wanted our test subjects to complete the experiment multiple times this experiment required simple to use, efficient interfaces to ensure a user's continued engagement. The experiment captures user Affective state using Mehrabian's [32] Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness (PAD). The user is requested to self-report their affective state using a popular psychological tool developed by [33] called the Self-Assessment Manikin (SAM). This three factor graphical scale provides a quickly understood, effective user interface, which directly transfers to the three dimensional PAD scales. Note that each scale is measured from one up to five with five being the maximum value. Figure 1a is a screenshot of the Android implementation showing the three SAM scales.

The user is then presented with context statements related to their behaviour and physical environment. We limit the focus on physical contexts in order to understand the impact of disruptive situations i.e. where adverse conditions can affect our perceptions of a situation and potentially our approach to dealing with them. These contexts comprise of i) level of noise; ii) amount of distraction; and iii) amount of activity. Users are requested to rate themselves for each using five point psychometric Likert scales from 1 to 5. Figure 1b shows the interface for collecting the different contexts. Popup labels presented upon selection are as follows:

(i) Noise - Very quiet ~ Very noisy
(ii) Distraction - No distractions ~ Far too many distractions
(iii) Activity - Not active at all ~ Very active

A total of twenty-six high-involvement products were used for the two experiments: Houses, Cars, Computers, Laptops, Mobile phones, Books for education, Jewellery or watches, Hotels, Holidays, Airline tickets, Car insurances, Life insurances, Bicycles, Televisions, Music CDs, Film DVDs, Hi-Fi stereos, Champagnes, Washing machines, Fashionable clothes, Health care packages, Cosmetics, Sofa suites, Fridge freezers, Home broadband packages and Video streaming packages. The product names were simply listed in a grid for the user to select, Figure 2a. For each iteration the user selects four products. Note that the user could not select this item again until all products had been reviewed, which ensured that the review of the products was reasonably distributed.

Once the products are selected the user submits their purchase-decision involvement utilizing Mittal's PDI scale [34] for each. The scale is very simple to replicate and comprises of three questions that determine the user's view on how much they care about a product, whether it is important to make the correct choice and whether they were concerned with the outcome of making that choice, see Figure 2b.

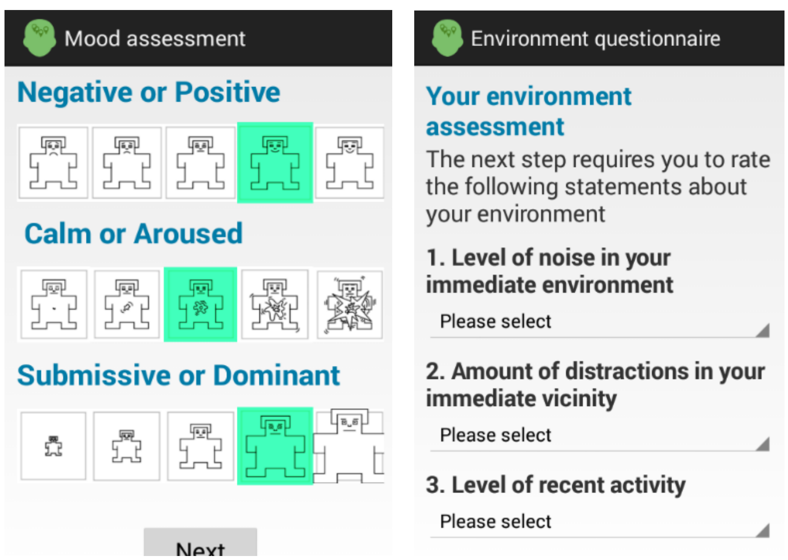

FIGURE 1: Two SiDISense user interfaces, a) Self-Assessment Manikin representing Mehrabian's PAD affective scale, b) Likert scale capturing levels of user perception of noise, distractions, activity and number of people.

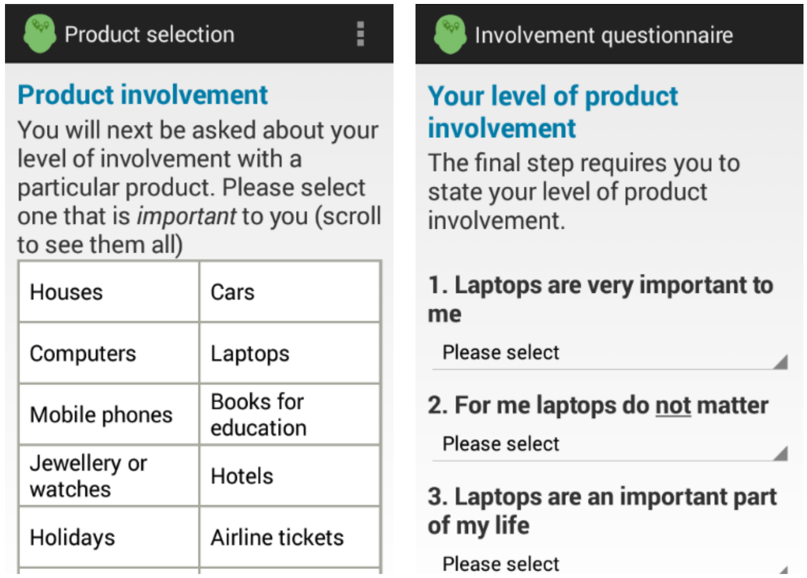

FIGURE 2: Two SiDISense user interfaces, a) selection of products, b) rating of products using Mittal's PDI assessment tool.

To support the assessment of the information gathered on PDI we also captured the user's current Product Involvement using the three point scale developed by [35]. This tool provides an insight into a user's enduring and situational involvement with a product. It will provide a benchmark in some of the analysis to determine the effect on the relationship between PDI and Product Involvement as disruptive contexts are introduced.

The products are shown with no information or images so feedback is based upon existing subjectivity on the product. For each assessment cycle the four products selected are randomised before being presented. Once the survey is completed the application encrypts and uploads the file to a secure server. SiDISense then resets and waits for the next notification point which the participant can adjust via a management interface.

The SiDISense application was distributed via Google Play to University staff and students using email and the University's virtual learning platform. In addition to this friends and family were contacted via Facebook with a request to participate.

5. RESULTS AND ANALYSIS

This section presents results of the two experiments for measurement of levels of Purchase-Decision Involvement (PDI). From the twenty users participating in the initial experiment 277 usable individual results were produced, with 60% of responses completed by female participants. The spread of age groups was as follows: 21 years and under (4%), 22 to 34 years (33%), 35 to 45 years (11%), greater than 45 years (52%). For the second iteration of the experiment a total of 364 submissions from twenty-four participants were collected with 64% of responses completed by female participants. The spread of age groups was as follows: 21 years and under (6%), 22 to 34 years (22%), 35 to 45 years (14%), greater than 45 years (58%).

Though we seek strong correlation for our results we obviously do not expect perfect values and hold with the general opinion that correlations of 0.3 are acceptable. For our hypotheses we test for two-tail correlation, the results of which are represented as r (result). The probabilities of these are measured using p-values and where statistical significance is shown as $p < .05$ (confidence level of 95%) or $p < .01$ (confidence level of 99%). To test the null hypothesis that the sample population means are the same we use the Two Independent Sample T-Test (1).

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{S_P^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}} \quad (1)$$

Upon first analysis of the full dataset produced in experiment one we find no correlations between affective state and levels of PDI (pleasure r=0.092, arousal r=-0.019, dominance r=0.092). However, where different contexts increase in value, significant positive correlations are produced. Table 1 presents results for both high and low values for contexts of activity, noise and distraction and combinations thereof. Results show that all three PAD scales produce some evidence of positive correlations as these contexts increase in value, however it is a user's level of dominance that produces the largest, and most significant, correlations with PDI.

Tables 2 and 3 further emphasise these findings by showing that as user Product Involvement decreases a user's dominance produces a significant correlation with PDI where disruptive contexts of activity and distractions are high. Knowledge of the user's Product Involvement will not always be available even if online marketing techniques do have a strong insight. The results suggest that user dominance is shown to be the most reliable axis of affective measurement, when using PAD, to determine the level of user PDI when adverse values in disruptive contexts are present, therefore we can reject the null hypothesis for *H1.*

We can then see a strong indication that user dominance and high activity produces a category split between both high and low PDI. A system could in effect rely on these two levels of logic to provide insight into user behaviour and adjust marketing strategies accordingly. However, further insight is provided when additional context is considered, i.e. disruptive contexts of noise and distractions. It is noted that as disruptions increase then so do correlations for PDI when activity is high. Low activity does not produce any correlations for PDI, whether other disruptive contexts are present or not, so we should assume that a system would need to determine whether to advertise through other means. The above results can be represented using a set of rules for utilisation in a system that determines when to place a product placement, i.e. choosing to advertise when PDI is high, see Figure 3.

		Pleasure		**Arousal**		**Dominance**	
Context	***Value***	**result**	**p-value**	**result**	**p-value**	**result**	**p-value**
Activity	> 3	0.234	> 0.05	-0.001	> 0.05	0.272	< 0.05
Distractions	> 3	0.324	> 0.05	0.237	> 0.05	0.380	< 0.05
Activity Distractions Noise	> 3 > 2 > 2	0.200	> 0.05	0.250	> 0.05	0.470	< 0.05
Activity	<= 3	0.031	> 0.05	-0.002	> 0.05	0.034	> 0.05
Distractions	<= 2	0.089	> 0.05	-0.078	> 0.05	0.024	> 0.05
Activity Distractions Noise	<= 3 <= 3 <= 3	0.02305	> 0.05	-0.032	> 0.05	0.042	> 0.05
Activity Distractions Noise	<= 3 > 2 > 2	-0.125	> 0.05	-0.166	> 0.05	-0.07	> 0.05

TABLE 1: Correlation between PAD and Purchase-Decision Involvement. High context values produce strong correlation for user dominance (significant values highlighted).

			Pleasure		Arousal		Dominance	
Context	**Value**	**Product Involvement**	**result**	**p-value**	**result**	**p-value**	**result**	**p-value**
Activity	> 3	All	0.234	> 0.05	-0.001	> 0.05	0.272	< 0.05
		>= 12	0.341	< 0.05	-0.157	> 0.05	-0.114	> 0.05
		< 12	0.231	> 0.05	0.384	> 0.05	0.590	< 0.01
		< 10	0.180	> 0.05	0.557	< 0.05	0.654	< 0.01
		< 8	0.251	> 0.05	0.658	> 0.05	0.876	< 0.01

TABLE 2: Correlation between PAD and Purchase-Decision Involvement where user activity is high show that the correlation increases as Product Involvement decreases (significant values highlighted).

			Pleasure		Arousal		Dominance	
Context	**Value**	**Product Involvement**	**result**	**p-value**	**result**	**p-value**	**result**	**p-value**
Distractions	> 3	All	0.324	> 0.05	0.237	> 0.05	0.380	< 0.05
		>= 12	0.336	> 0.05	0.114	> 0.05	0.224	> 0.05
		< 12	0.472	> 0.05	0.420	> 0.05	0.586	< 0.01
		< 10	0.427	> 0.05	0.479	> 0.05	0.633	< 0.05
		< 8	0.752	> 0.05	0.934	< 0.01	0.931	< 0.01

TABLE 3: Correlation between PAD and Purchase-Decision Involvement where distractions are high show that the correlation increases as Product Involvement decreases (significant values highlighted).

For the first experiment we apply the logic that categorises the data into *context-aware-advertised* and *context-aware-not-advertised*, which produces 13.38% and 11.15% average mean respectively. This is a 16.67% increase in favour for context-aware advertising. Applying the two sample t-test to these values produces a significant difference of means d = 2.23, p = 0.047. This result demonstrates that while the correlation analysis could be suggested as a weak method on which to define the model, the use of this contextually aware logic results in identifying a group of instances with a high mean of PDI.

To be able to suggest that running a context-aware system would produce better results than a non-context-aware system that simply always presented the product, we ran the experiment again, except that in this iteration of the experiment we created two datasets by randomly placing the participants into one of two groups of data. This method produced a *context-aware* and *non-context-aware-advertised* dataset. The *non-context-aware-advertised* system does not know the user's PDI and always advertises, and the *context-aware* system chooses when to advertise using the code presented above. Using these datasets we not only compare the logic that produced the split into *context-aware-advertised* and *context-aware-not-advertised* categories using the context-aware data but also compare the *context-aware-advertised* data to the complete set of *non-context-aware-advertised* data.

```
if (activity > 3) {
  if (distractions > 3 and noise > 3) {
    if (user_dominance > 2) {
        advertise = true;              // PDI is higher

    } else {
        advertise = false;             // PDI is lower
    }


  }
} else {
     advertise = false;            // PDI is non-predictable
}
```

FIGURE 3: Logic for determining when to place an advert.

The values produced in the second experiment for *context-aware-advertised* and *context-aware-not-advertised* and *non-context-aware-advertised* are 13.33%, 11.53% and 11.53% respectively. Again making the comparison between *context-aware-advertised* and *context-aware-not-advertised* we see a significant percentage increase of 15.6% and difference of means values of d = 1.8, p < .02, in favour of where adverts are placed. To assess the value of context-awareness against a static always advertise system we then compare the average mean for *context-aware-advertised* and *non-context-aware-advertised.* We again use the two sample t-test and see a significant increase in favour for the context-aware system with values of a 16.1% percentage increase and difference of means values of d = 1.85, p < .02.

While the percentages are seemingly low, this increase in potentially successful user engagement would make a significant impact over time when considering the volume of advertisements associated with m-commerce. Based upon the results above we can state that using a context-aware system to determine when to engage someone based upon their level of PDI is possible, and we can therefore reject the null hypothesis for *H2.* The following section discusses the implication of these results.

6. DISCUSSION

It is clear from our own and other research results that cognitive phenomena, e.g. the forming of purchase-decision involvement are reliant upon aspects of our affective state. Indeed there are many research findings that indicate that mood and emotions are directly related to cognitive phenomena [36]. In particular a user's level of pleasure has been shown to be key to findings related to on-line marketing [37], the browsing for information, and the purchasing of products [38]. Alongside this our results however have identified that user dominance can also be an important factor in mobile device user's cognitive processes. This finding aligns itself with other research statements that user dominance is as legitimate as pleasure and arousal scales and should not be ignored when considering consumer behaviour and retail marketing [18]. Broekens [19], also advocates the importance of dominance in modelling or measuring affect and that aspects of dominance, e.g. power, control, approach vs. avoidance and coping potential, must be considered. Emotions that clearly sit along the scale of dominance, e.g. anger or fear, have been shown as important where perception of risk is involved and that this is linked to influencing decision making in highly differentiated ways [39]. Online shoppers could also be relying upon dominance to maintain control of their shopping situation by choosing online rather than traditional retail outlets [17] and with high control (dominance) are more likely to respond to sales or bargains [40].

Having an insight into the importance of understanding dominance in mobile device users may be beneficial in many sectors. On-line marketing currently relies upon different methods of drawing a potential purchaser's attention. These methods can rely upon influencing emotion either through manipulation [41] or the use of ‘priming’ which presents the device user with different stimuli intended to influence the response to a later stimulus i.e. the final advert, [42]. While advertising techniques are tried and tested within traditional and online marketing, these tend to focus upon levels of pleasure and arousal [43], [24], [44], [45]. The inclusion, if not the sole focus upon user dominance could be a benefit to advertisements presented via smaller mobile devices, especially where the device user is potentially outside areas of comfort e.g. browsing on the device in an unfamiliar location.

This premise would also apply to recommender systems. Armed with the knowledge of a consumer’s level of dominance and whether a purchase requires higher dominance due to specific information associated with a product, i.e. an element of risk, the system could determine whether to make an alternative recommendation or not. This is in effect a context-aware recommender system (CARS) utilising the context of the consumer’s level of dominance to support a traditional recommender system in the decision making process. Previous work into CARS have aimed to determine the level of emotion or mood within the consumption phase of the item recommended. For example, if someone enjoys a film that they have watched (consumed) then the recommender system will recommend similar films that have produced similar enjoyment, this film would also be recommended to other viewers looking for the same level of enjoyment [46]. This process is based upon methods of simple human observation where we determine suitable items through previous behaviour [47]. Existing mood can also affect how the consumer will rate items, because they are in the right mood to enjoy it and not just because they are interested in it [48]. This suggest that predetermined mood or emotions can influence the method of system-user engagement and aligns with our hypotheses and research findings in determining how to engage with a user.

One of the main focusses of this research has been to show how situational disruptions impact upon cognitive processes, e.g. the forming of purchase-decision involvement in a mobile context. Our results demonstrate that higher levels of disruptions exposed relationships between purchase-decision involvement and affective state, in particular levels of user dominance. In other words while no relationship between purchase-decision involvement and a mobile user’s dominance is expected when levels of disruptive contexts are low, as disruptions become more intense the level of purchase-decision involvement increases as dominance increases. This can be interpreted to say that a mobile user with low dominance who is subject to high levels of disruptions will not make a suitable target for high involvement product advertisements. Park et al., [49], demonstrate that while strong, negative, emotions encourage cognition, weak emotions were not conducive to advertising transmitted via the mobile device. This suggests that both the forming of high purchase-decision involvement is not possible for users experiencing weak emotions and aligns itself with our findings that low dominance in mobile users lead to low levels of purchase-decision involvement.

The insight gained from our findings demonstrate that disruptive contexts have an impact upon our behaviour with high disruptions providing an opportunity to model cognitive capabilities for use in e-commerce. This aligns itself with previous research in to physical contexts and their effect upon behaviour. Research has shown that focusing upon activities that have been previously learnt rather than learning new tasks would be more successful when noise levels are higher [50], however the disruptive effect of noise is not necessarily dependent on its volume, loud music is not detrimental to everyone to the same effect at the same time. Ünal et al. [51] identify that listening to music whilst driving a vehicle does not affect the driver’s capability and that it is possible that even though there is an increased mental effort due to the distraction caused we can mediate the effect in situations requiring sustained attention. It is also apparent that people differ in their ability to focus when attempting tasks, some need quiet to completely engage whereas others prefer to have background noise in the form of music or even from a television show. As our findings show the above suggests that noise cannot be considered of its own accord but together with other contexts.

Distractions have been shown as important with research into the issues of environmental distractions focussing upon their impact work and learning activities. Distractions to the knowledge worker are acknowledged as a prime issue that prevent tasks being completed effectively [52]. Distractions also have an impact on learner's concentration, however, a context recommender system that focuses upon activities that access previously learnt knowledge rather than learning new material would be more successful when distractions are higher [50]. Previous work has also attempted to use recommender systems to filter out distractions that cause delay in completing tasks or aid the re-finding of previously accessed information this method is reliant upon contextual information to be effective [53]. Demonstrating that distractions can be 'managed out' provides further support to our hypothesis that disruptions contribute to our cognitive capabilities and can therefore be modelled. Therefore, not only could a context-aware recommender system use pre-filtering so that only specific information that is suitable to the tasks completion is recommended [53] but by providing the recommender system with the worker's cognitive capability or pre-disposition, then further filtering or more appropriate filtering could be applied.

As well as being environmental, distractions can also be present in the form of physical pain and can impact upon someone's ability to focus or complete tasks [54]. Distractions such as music are used however in the treatment of pain [55] therefore while being a potential distraction music could also be the facilitator in being able to focus on a tasks. So while distractions can manifest themselves in many ways, including audio, visual and physically, they are also task related. Depending upon how distractions manifest themselves can determine the person's capability in certain tasks. For example when compared to listening passively to music the activity of sending a text using a smart-phone can increase a person's reaction time to a secondary task because of the increased cognitive load [56]. Again this point highlights that situational contexts related to task distraction are complex and are reliant upon an individual's situation. This suggests that a core model that adapts to the individual over time may be essential for environmental and behavioural context to be truly effective.

As a disruptive context we see level of activity as perhaps the most important context explored in this research. Not only did activity standout as an individual context that effected the relationships between affective state and the cognitive phenomena explored but it also accentuated the effect of other disruptive contexts upon these relationships. The context of physical activity proved to be very influential upon the findings within this research even without considering particular labels, e.g. walking or running. Though we capture a subjective level of recent activity this does not mean that the level of activity could not have been maintained for a longer period of that associated with the term 'recently'. Even though the subjective readings did not fully capture a complete description of the participant's activity it did provide enough detail from which to determine an insight into its relationship with other contexts. We see that depending on the level of the user's activity, i.e. high vs. low, other user contexts become more important in forming levels of purchase-decision involvement or perception of information presented via a mobile device. This provides an insight into the complex relationship between physical activity and cognitive capability and in particular reflects previous findings that high levels of activity will improve our cognitive function [31] [57].

Even though a mobile user's situational context is diverse, the results are testament to the fact that even modelling a low number or disruptive contexts is enough to capture the effect sought. However this discussion highlights that behaviours arising from situational contexts are complex and is not trivial to model effectively. Therefore the inclusion of additional disruptive contexts would undoubtedly increase the performance of the model as would any context that provided insight into the consumer-product and the consumer-environment relationships.

7. CONCLUSION

This report provides insight into consumer likelihood of engagement which can be used for developing m-commerce strategies for smart-devices. The findings presented here show that application of user context can be used to determine the level of user purchase-decision involvement. We find that disruptive contexts, i.e. user activity and distracting environment contexts, are important factors in forming this cognitive process which is particularly important for establishing a user's purchase mind-set.

As predicted we also found that the affective scale of user's dominance-submissiveness proved to be as good as, if not more reliable, than the measurement of the pleasure-displeasure scale when attempting to gain an insight into user cognitive processes and decision ability. This finding provides further insight into not only cognitive processes but also the relevance and potential to managing engagement with mobile device users.

Most importantly, high activity and low user dominance together are an indication that a user has low purchase-decision involvement and therefore potentially low likelihood of engaging in the purchasing cycle. Our findings also show that contexts of noise and distraction have also impacted on correlations between user affect and purchase-decision involvement with high disruptions decreasing further the low purchase-decision involvement. These findings are an indication of when a consumer is potentially willing to engage but the disruptions could be preventing them from doing so, and highlight the need for such a model to determine when to engage the device user.

This study has limitations in that the findings herein rely on the use of subjective feedback of various contexts. Future research will focus on the measurement of contexts using smart-phone sensors in an attempt to establish accurate readings that reflect the individual's perception. The model also requires the measurement of user affective state, which is a complex task and while many research attempts have been made, there is no de-facto method that can be employed. Therefore future research will be required to measure PAD, in particular user dominance, for the model developed to become fully autonomous.

To conclude, our main contribution is to have widened the understanding of a number of user contexts and their influence upon smartphone user behaviour towards high involvement products. We have also shown further evidence that disruptive contexts including noise, disruptions and activity should be considered when developing m-commerce context-aware systems and have presented a method for engaging with consumers using smart devices.

8. REFERENCES

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