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           into Mobile Commerce Systems

Name: Mark Hooper

LEVERAGING CONTEXTUAL-COGNITIVE RELATIONSHIPS INTO MOBILE COMMERCE SYSTEMS

by

Mark Alan Hooper

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Academic Thesis: Declaration of Authorship

I, *Mark Alan Hooper* declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

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Abstract

Mobile smart 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 effective within the varied situations that mobile users encounter. Where traditionally a recommender system will focus upon the user – item relationship, i.e. *what* to recommend, in this thesis it is proposed that due to the complexity of mobile user situational profiles the *how* and *when* must also be considered for recommendations to be effective. Though non-trivial, it should be, through the understanding of a user's ability to complete certain cognitive processes, possible to determine the likelihood of engagement and therefore the success of the recommendation.

This research undertakes an investigation into physical and modal contexts and presents findings as to their relationships with cognitive processes. Through the introduction of the novel concept, *disruptive contexts,* situational contexts, including noise, distractions and user activity, are identified as having significant effects upon the relationship between user affective state and cognitive capability. Experimental results demonstrate that by understanding specific cognitive capabilities, e.g. a user's perception of advert content and user levels of purchase-decision involvement, a system can determine potential user engagement and therefore improve the effectiveness of recommender systems' performance.

A quantitative approach is followed with a reliance upon statistical measures to inform the development, and subsequent validation, of a contextual-cognitive model that was implemented as part of a context-aware system. The development of SiDISense (Situational Decision Involvement Sensing system) demonstrated, through the use of smart-phone sensors and machine learning, that is was viable to classify subjectively rated contexts to then infer levels of cognitive capability and therefore likelihood of positive user engagement. Through this success in furthering the understanding of contextual-cognitive relationships there are novel and significant advances that are now viable within the area of m-commerce.

Dedication

I dedicate this work to my family, Naomi, Molly and Peggy. Your patience, support and laughter made it all possible. Thank you.

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Abbreviations

A_{ad}	Attitude towards the Advert
AES	Advanced Encryption Standard
ANN	Artificial Neural Networks
CARS	Context-Aware Recommender Systems
PAD	Pleasure Arousal Dominance dimensional model
PDI	Purchase-Decision Involvement
RSA	Rivest Shamir Adleman
SAM	Self-Assessment Manikin

1. Introduction

1.1 Background of Study

Up until now there has been limited research into understanding the cognitive capabilities of mobile device users within different situational contexts or in using this knowledge in an attempt to improve the efficiency of e-commerce activities. Recent advances in technology now mean that typical smart-devices have on-board sensors that can be used to understand the device user's behaviour. This should make it possible to improve the use of e-commerce services within dynamic environmental situations by presenting appropriate product advertisements that suit the device user's immediate cognitive capabilities. This thesis examines how modern smart-device technologies can be leveraged to enable e-commerce systems in producing a more effective user purchaser conversion rate, i.e. produce an increase in product sales and provide more realistic services to mobile device users while engaged in continuously changing environments.

Consumer purchasing traits including, motivation (Rohm & Swaminathan, 2004), impulse buying (Youn & Faber, 2000), brand attitude (Myers & Sar, 2015) and risk-taking (Brave & Nass, 2002) are well known concepts but as yet not fully realised within e-commerce activities, and in particular, Context-Aware Recommender Systems (CARS). This is the focus of this research. This research explores the theory that affective state, i.e. mood and emotions, influence our cognitive capabilities in processing information, which in turn will provide an insight into levels of message persuasion and potential decision outcomes. Similarly, also explored are situational contexts in order to show that they can be used to understand the relationship between user affective state and cognitive capabilities. Both concepts are novel and provide exciting opportunities for improving e-commerce and recommender system performance.

Research has shown that our mood and emotions influence the selection of cognitive processing modes when we assess information (Gebhard, 2005). It is generally agreed that positive mood results in reduced capacity and therefore a favouring towards heuristic processing, i.e. Mental Imagery, whereas negative mood will facilitate more complex detail analysis (Martin, 2003). Myers and Sar,

(2015), present insight into how a pre-existing mood affects a user's response to different methods of information presentation in advertisements. They describe how positive evaluation of an advert is enhanced by a positive mood through increased ability to undertake mental imagery processing, however, there remains the capacity to evaluate detailed information during periods of negative mood. In contrast, an analytical processing style is used to thoroughly understand details of the purchasing situation and so identify all important information and potentially limit risky consequences (Burroughs, 1996). The selection of the style of cognitive processing is therefore dependent on the characteristics of task, stimulus and the individual consumer (Burroughs, 1996).

While considering styles of information processing, risk acceptance and levels of processing effort will support the delivery of effective e-commerce solutions it should also be emphasised how common techniques for manipulating emotions are important in marketing campaigns. Emotional appeals are used to create a psychological reaction that provides a call-to-action in the appeal message (Hastings, Stead, & Webb, 2004) and can be used to support the delivery of effective e-commerce solutions. Positive appeals, which present assured messages, are used to engage emotions like love, desire or humour to invoke psychological phenomena such as self-esteem (Robberson & Rogers, 2006). Fear appeals however, are also common in advertising and focus on user insecurity in order to prompt action. Success is varied for this technique as it is reliant on the content and severity of message (Hastings et al., 2004), however it also seems probable that user mood, for example, will also be a factor in determining the outcome. It is therefore postulated that while different advertisement techniques can leverage user traits and influence purchasing behaviour, the advertiser should also consider that user context, including mood and emotions, will have an effect upon behaviour. In this research it is also suggest that because of the range of different information processing styles available, and the complexity of user situations, it is difficult to be certain which is the most applicable at a single point in time, especially for systems aimed at mobile consumers.

In terms of user interactions the use of mobile devices within an e-commerce context is a special case. Evidence is presented (Holmes, Byrne, & Rowley, 2014) that mobile devices are used for product information search, review of alternatives and purchase activity, especially for high-involvement

products. These activities not only take place at home but also at retail locations, when travelling and simply when 'out and about'. 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 (H. S. Kim, 2005). Alongside this construct, Purchase-Decision Involvement, as defined by (Mittal, 1989), is a concept used to capture the user's mind-set towards an anticipated purchase, ideally this is measured as close as possible to planned marketing events. In addition to general understanding of product preferences, e.g. product involvement, understanding a user's purchase-decision involvement 'on the fly' should also be a valuable component to m-commerce campaigns.

To be effective in delivering such functionality to dynamic systems the measurement of mood and emotions is critical. Affective computing involves computational methods for understanding user mood and emotions. There are many theories that have been developed to define these phenomena, each have a different focus which depends on specific attributes of a study's requirements (Scherer, Banziger, & Roesch, 2010). Dimensional theories however 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 thus providing a space within axis of specific states where affective state can be modelled. The three dimensional axis of Pleasure-displeasure, Arousal-nonarousal and Dominance-submissiveness (PAD) (Mehrabian & Russell, 1974), is a dominant dimensional model which has been shown as an effective method of modelling emotions and other affective states (Marsella, et al., 2010). Examples where PAD has been successfully used in a mobile device context include (Heudin, 2004), (Helfenstein, 2005) and (Ferwerda, Schedl, & Tkalcic, 2015). This approach is therefore adopted within this research to enable the modelling of emotions and affective states.

While the use of PADs Pleasure and Arousal dimensions are prevalent in research some authors suggesting that the axis of dominance does not have a significant effect on behaviour (J. A. Russell & Pratt, 1980), (Ward & Russell, 1981). Positive emotions are also widely attributed as the control in user decision making within complex situations (Alice M. Isen, 2001) (Ashby, Isen, & Turken, 1999). Others however have suggested that dominance may be more relevant within the online retail

context (Eroglu, Machleit, & Davis, 2001), in addition to this it is understood that dominance is also potentially relevant where the environment is an issue (Machleit & Eroglu, 2000). From this it is postulated that while many research efforts ignore the dimension of dominance it is important that a holistic approach is adopted when considering user affective state for the development of m-commerce systems.

A user perception of dominance or 'control of situation' is related to judgements based on environmental stimuli and so determines their emotions and behaviours (Koo & Lee, 2011). This suggests that decision processes may become more complex as situations become more physically challenging. The mobile user could be required to access different layers of trust, for example, for both information presented via the device and the actual physical 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 (Broekens, 2012). 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 would in a controlled, familiar situation. This concept warrants further research if e-commerce is to truly become context-aware and effective upon a mobile platform.

While the notion is commonly understood, there has been little research into relationships between affective state and cognitive capabilities and how they are affected by situational contexts in order for this knowledge to be implemented within an e-commerce system. Environmental contexts also have an impact on the user's preferences (Adomavicius & Tuzhilin, 2015) as well as our ability to process information or make decisions. So while typical mobile devices are small and designed for an 'on the move', multi-tasking lifestyle, it is likely that due to their situation users may not always have the ability or intention to undertake more demanding or sensitive tasks (Mallat, Rossi, Tuunainen, & Öörni, 2009).

The physical environment has been shown to be crucial in mediating emotional and behavioural responses because of their effect on our perceived control over the situation (Hui & Bateson, 1991).

Therefore increases in extremes of environmental contexts including crowding (Hui & Bateson, 1991), interruptions (Speier, Vessey, & Valacich, 2003) and noise (Banbury & Berry, 2005) are all likely to have an effect on behaviour by affecting cognition ability. Environmental stressors such as noise and overcrowding can effect both behaviour and the evaluative aspects of cognition (Guski, Felscher-Suhr, & Schuemer, 1999), as do distractions (McGehee, 2014). High levels of activity have been shown to improve our cognitive function (Hogan, Jutta, & Carstensen, 2013) (Erickson, Hillman, & Kramer, 2015), however it is unknown whether a lack of recent, short term, activity could be detrimental to cognitive capability and therefore reduce the likelihood of positive engagement with e-commerce services.

So while a mobile device user may perform tasks in a preconditioned way based upon general habits, other situational contexts should be considered independently (Mallat et al., 2009). A user may associate different locations with different emotions (Rachuri et al., 2010), (Ma, Xu, Bai, Sun, & Zhu, 2012), or seek particular places to undertake tasks (Holmes et al., 2014), however these are still choices selected via experience or habit. It is however probable that other situational contexts associated with a particular location will influence the current mood and produce varied emotions which will affect user behaviour and ability in completing a task. It is postulated that physical contexts not only have an impact on the user's preferences (Adomavicius & Tuzhilin, 2015) but will also influence user ability to process information (Chang, 2002) and decision control (Hui & Bateson, 1991). Therefore this is a research area that should be considered further to understand the relationship between user and physical environment for implementation within m-commerce.

Traditional e-commerce systems, in particular recommender systems, focus upon *user preferences* and *items*, with little consideration for additional contextual information such as time or place (Adomavicius & Tuzhilin, 2015). However Context-aware Recommender Systems (CARS) are developing in their capacity for informing an e-commerce system's decision for making recommendations. Many context have been researched, including but not limited to, physical constraints that include weather, user disability, timing and budgeting for meals or breaks (Gavalas, Konstantopoulos, & Mastakas, 2014), methods of transportation (Saiph Savage, Baranski, Elva

Chavez, & Höllerer, 2012), patterns of user mobility (Gavalas & Kenteris, 2011) and social environment (Gavalas & Kenteris, 2011).

Contexts of user mood and emotions have also been established as important to recommender systems (Adomavicius et al., 2011) primarily because they are closely related to the user's experience (Tkalčič, Burnik, & Košir, 2010). However, most efforts have focused upon the use of user 'emotional intelligence', i.e. self-understanding of own emotions (González, de la Rosa, Montaner, & Delfin, 2007), 'user allocation' of mood to an item i.e. a particular song (H.-S. Park, Yoo, & Cho, 2006) and 'mood information' tagged within an item's profile (Andjelkovic, Parra, & O'Donovan, 2016) or where emotions are expressed or extracted from content within blogs etc. (Fernández-Tobías, Cantador, & Plaza, 2013). The issue is that CARS do not currently take into consideration the user's cognitive capacity before making the recommendation. This is an unaddressed challenge but is important due to the variability of the mobile user's situation. So, while traditional methods identify particular products that a user may be favourable towards, if their situation means that for whatever reason, they are unable to make decisions comfortably, the product placement is likely to be unsuccessful. This is obviously an issue for businesses that are paying for their online advertisements used been approached for placing popular, higher cost products.

User personality can also determine user preference, which can be used to personalise appropriate recommendations (Ono, Kurokawa, Motomura, & Asoh, 2007). Perception is also important in that user perceived effort and the system's effectiveness will affect success rates Knijnenburg, Willemsen, Gantner, Soncu, & Newell, (2012). However research into user perception has typically focussed upon areas including perception of system performance (Pu, Chen, & Hu, 2011) and perception of transparency of the system (Sinha & Swearingen, 2002). Research into the user's actual perception of information provided by an e-commerce system, i.e. a recommended item, has not, until now, been approached. So while physical and modal contexts are being used within recommender systems for making appropriate recommendations they, thus far, do not use contextual information to determine cognitive behaviours towards the recommendation. Without this understanding the knowledge of what is influencing levels of user engagement will be limited and is thus the focus of this research.

To consider the above it is important to also discuss methods of collecting user data for use with an e-commerce system. The use of smart devices is prolific across most demographics but are also useful tools for modelling user contexts. Through the use of on-board sensors, phone applications have been used to gauge mood (Ma et al., 2012), stress (Giakoumis et al., 2012) and exercise (Consolvo et al., 2008). Sensors have also been used to measure environmental context such as ambient noise, levels of music and speech in order to determine user issues such as stress (Lu, Campbell, & Gatica-perez, 2012). Smart-phone sensors and phone applications, e.g. email, SMS and social networks, have also been used to map user's phone use patterns and the content of their communication to support the capture user of mood (Likamwa, Liu, Lane, & Zhong, 2011), (Ma et al., 2012). The smart-phone microphone is a valuable tool and can be used to classify specific situational environment noises (Lu et al., 2009) (Delgado-Contreras et al., 2014). Another important sensor, the accelerometer is used for measuring patterns of movement, including user gait (Nishiguchi et al., 2012), activities such as jogging, walking, sleeping (Kwapisz, Weiss, & Moore, 2011), all of which can provide insight into user behaviour.

To effectively undertake data classification requires working with live data, and this can become a real issue for small devices (Lane et al., 2010), therefore care when working with real-time data is needed to reduce issues of over-burdening available computational resources (Emiliano Miluzzo et al., 2008). Consideration needs to be given to issues of continuous sensing and real-time results (Lu et al., 2010) and to the post-processing of the data which requires lightweight classification algorithms (Lu et al., 2009). Even though smart-devices are constantly increasing in their processing capacity because of the amount of real-time data that is required for modelling user behaviour and other contexts this issue provided a focus to be addressed as part of this research.

So, while research has had success in using smart-phones to develop personalised models, the continual updating of contextual information can produce a considerable draw upon resources and make the device unresponsive. There are however many instances that demonstrate the benefit of contextual modelling and with balanced need-frequency management and careful choice of post-processing methods, it is possible to reduce the impact upon normal use. Care and consideration to

these issues will enable research into the above challenges that relate to the use of environment and user contexts for improving e-commerce user focussed services.

1.2   Problem Statement

Research into improving the effectiveness of recommender systems has recognised the importance of context (Adomavicius & Tuzhilin, 2015). However m-commerce systems that focus on user perceptions of environmental contexts and their effect on consumer behaviour have received little interest. So while use of user contexts are becoming more prevalent on-line there is limited knowledge of how situational contexts actually affect user cognitive behaviour and therefore user interactions with m-commerce activities.

These context related behaviours are potentially key to the success of commerce activities within a mobile context and as we and technology become increasingly mobile this lack of insight is potentially hindering the development of effective mobile user engagement and the future success of growth in m-commerce. This gap in knowledge is the focus of this research.

1.3   Objectives and Motivation

This research's aim has been to demonstrate further the understanding of how situational context influence an individual's cognitive capabilities and attitudes. Secondary to this is to produce a model of engagement that will aim to increase the yield of e-commerce systems, namely recommender systems, by determining a user's levels of engagement with information (product marketing) as presented via a mobile device.

To do this an investigation into cognitive processing modes, e.g. perception of information presentation styles and formation of purchase-decision involvement, together with how they change whilst using a mobile device within everyday activities is a key component of this research. It is posited that understanding user behaviour and cognitive capability is critical in order to fully realise the potential for mobile recommender systems and m-commerce.

To facilitate this an additional layer to the traditional recommender system model is proposed in order to determine the 'how and when' aspects of engaging with a user. This concept supports the process of effective placement of advertisements which provides an edge to m-commerce marketing campaigns through the increase of user activity, be it purchasing or brand awareness.

The research focuses around the following key aim:

I. To establish a model of behaviour realised through the analysis of user affective states and local environment contexts to surpass the effectiveness of current context-aware recommender systems.

The full objectives are identified as:

I. Investigate information perception and purchase-decision involvement for high-involvement products to understand their relationship with mobile device user's affective state;

II. Define a novel model that models user affective-environment context relationships for use with recommender systems;

III. Develop a novel, proof of concept software solution that implements a context-aware system that utilized both user and environmental contexts to demonstrate effects upon user engagement which could then be used as a preliminary phase to a recommender system process, i.e. whether to make the product placement and then adopting the best method for engagement.

From the above a focus was applied to three research questions that if answered positively would lead the way in supporting the development of context-aware recommender systems with an advanced capacity for improving the effectiveness of e-commerce systems.

This research thus follows three key questions:

I. Can a context-aware system using both user and environment contexts be able to determine what style of product placement is suitable for a high involvement product or service?

II.   Can a context-aware system using both user and environment contexts be able to determine when to make a product placement for a high involvement product or service?

III.   Will a context-aware system using both user and environmental contexts achieve higher levels of user engagement than a non-context-aware system if armed with the capabilities of hypotheses in I & II?

To address these research questions the following initial hypotheses were developed to guide the researcher over the full period of research. Note that each *null hypothesis*, e.g. H_0Ia, is followed by its corresponding alternative hypothesis, e.g. H_1Ia.

Research question I hypotheses (a and b)

H_0Ia: An increase in positive user affective state will not correlate with an increase in positive perception of a writing style requiring high cognitive effort.

H_1Ia: *There will be a positive correlation between a user's perception of a written statement requiring high cognitive effort and the user's positive affective state.*

H_0Ib: That increases in extremes of disruptive context will not introduce an increase in correlation between positive user perception and user affective state.

H_1Ib: *That an increased level of positive correlation between dimensional scales of affective state and positive perception of different advertising styles will be achieved when we are subjected to disruptive contexts.*

Research question II hypothesis

H_0II: That increases in extremes of disruptive context will not introduce an increase in positive correlation between user purchase-decision involvement and user affective state.

H_1II: *That an increased level of positive correlation between dimensional scales of affective state and purchase-decision involvement will be achieved when we are subjected to disruptive contexts.*

Research question III hypothesis

H_0III: That a system which favours the use of disruptive context-aware logic over non-context-aware logic will not see any statistical advantage.

H_1III: *That a statistically significant increase in average mean will be achieved for both user PDI and user perception when a system favours the use of disruptive context-aware logic over non-context-aware logic.*

1.4   Research Methodology and Implementation

A non-experimental quantitative approach was applied during this research. This approach examines variables as they exist (Belli, 2008), utilising numeric, empirical data and is considered to provide objective and structured observations (Punch, 2013). The benefits of using non-experimental research is that large amounts of varied data can be collected with relative ease, within a realistic setting, and the resulting significance of findings is achieved through multivariate statistical analysis (Tayie, 2005). The research herein uses statistical methods, including correlation analysis, to indicate potential relationships. Whilst these do not provide definite cause it can be suggested as a likely conclusion for a causal relationship through careful consideration and presentation of logical arguments (H. A. . Simon, 1954).

The reader should note that while the work conducted herein falls within non-experimental research the term *experiment* is used throughout as an identifier to each investigation undertaken. The term non-experimental refers to the methodology used whereas the general term of experiment simply refers to "a scientific test that is done in order to study what happens and to gain new knowledge" (Hornby et al., 2010) and is therefore referred to throughout as each section of work is presented.

Survey research, namely the self-administered questionnaire, is undertaken throughout this research to collect the sample data. Questionnaires are ideal for conditions where the intended population is too large and a representative sample is needed. This research implements these self-administered questionnaires using either paper-based or electronic methods. The electronic questionnaires comprised of on-line surveys and a bespoke Android application which was developed over time as requirements matured.

The initial experiment was a paper-based questionnaire which was administered in a classroom location. The consent forms, with attached questionnaire, were distributed to students who had agreed to participate. Apart from the initial paper-based experiment all survey participants were either University of Bedfordshire (Luton, UK) staff or students, invites were managed via email and the University's virtual learning platform. In addition to this friends and family were also contacted via Facebook with a request to participate. All prospective participants were sent an invite with a call to action, including a description of the project, a note on privacy and a link to the survey.

In collecting data the method of non-probabilistic sampling is followed, which, while suffering the issue of bias and lack of sampling frame (Farrokhi & Mahmoudi-Hamidabad, 2012), can be suitable for exploratory research design. There are a number of benefits to its use, e.g. it has low 'cost' considerations and provides suitable access to a broad range of participants as it does not focus on any specific user group (Etikan, 2016). Non-probabilistic sampling is also defensible if a precise experiment design audit-trail is provided (Farrokhi & Mahmoudi-Hamidabad, 2012).

The experiments undertaken as part of this research primarily rely upon a total of four previously validated instruments in the form of survey questionnaires (see Chapter three). These instruments are utilised throughout the research undertaken here:

I. Product Involvement (Laurent & Kapferer, 1985)

II. Purchase-Decision Involvement (Mittal, 1989)

III. User Perception utilising the semantic differentials method (Bruner, 2009)

IV. Pleasure-Arousal-Dominance emotional state model (Mehrabian, 1996).

In addition to these tools above a bespoke questionnaire was developed for this research. The focus of this survey instrument was to capture user environment and activity and was measured in a similar manner to the other tools using subjective feedback from the participant. This bespoke tool, the *disruptive situational context questionnaire*, is key to the novelty of this research, see section 3.7.4 for conceptual details.

The previously validated and bespoke instruments are combined into a single self-administered questionnaire designed specifically so there is no intervention between the researcher and the participant during data collection. Using this method enabled a number of different experiments ranging from paper based through to smart-phone applications without changing the style of the questionnaire or the participant-research relationship.

A purpose built Android application was developed by the author and was used throughout this research in different variations (see Chapter four). The application, SiDISense (Situational Decision Involvement Sensing System), developed from an early stage application, distributed questionnaire into a context-aware system for predicting user involvement and perception. The system encrypted all the results completed by the participants and uploaded the encrypted data to a secure server where it was decrypted for analysis. That data is anonymised through randomly generated user identification however this still enabled the participant to withdraw their data from the experiment at any point.

1.5   Significance of the Study

This research has focused on context-awareness and user cognitive behaviours in order to advance user engagement with e-commerce systems whilst using mobile smart devices. As a relatively unexplored area of m-commerce and recommender systems this work is important as it provides insight into how a situation's environment and user behaviour can influence cognitive capabilities and thus engagement.

This novel research demonstrates that while a user can have a high level of involvement with a product, if their situation means that they are unable to process the product information, for whatever

reason, the product placement will not be successful. This research is also important as by identifying a user's level of engagement a system can then take advantage by determining whether or not to place a particular product and to also potentially identify the best style of advert which would suit the user's current cognitive capacity.

The contributions will benefit research in a number of areas, including support for knowledge workers and on-line learning. The key area to benefit however will be m-commerce, the main contributions are listed as follows.

Contributions:

- a definitive context-aware prototype system that provides a framework for acquiring environmental and behavioural contexts and which uses machine learning for inferring levels of user cognitive capabilities and therefore estimate the likelihood of positive engagement with product placements in a m-commerce context.

- an increased knowledge of relationships between *affective state* and *cognitive capability*, including the forming of perceptions of information presented via a mobile device and the user's ability to form levels of purchase-decision involvement.

- the definition of the novel term *disruptive contexts* and their impact upon mobile device user's existing cognitive relationships.

- the identification of the importance of Mehrabian's (1996) dimension of *dominance* in m-commerce activities.

- the knowledge that user's subjective understanding of their environmental and behavioural contexts can be used to classify user cognitive capabilities in a mobile context using machine learning techniques.

- the identification that relationships between affective state and cognitive processes will differ depending on the type of computing device in use, i.e. a desktop vs. small mobile devices.

1.6   Thesis Roadmap

The remainder of the thesis is organised as follows:

Chapter two - focusses upon the Research Setting and Design Motivation for this research. Initially the theories of *dimensional models of emotion*, *consumer behaviour*, *user involvement* and *perception* of on-line product placement are introduced. In particular, dimensional models are explored with emphasis upon Mehrabian's (1996) three dimensional model of Pleasure, Arousal, Dominance.

Together with consumer behaviours and advertising techniques basic cognitive processes are then investigated. Decision processes associated with purchasing a product, e.g. *purchase-decision involvement* (Mittal, 1989), *user perception* and user *attitude towards the advert* (Lutz, et al., 1983) are introduced in order to provide a platform from which to inform an insight into consumer engagement with product appeals.

Chapter two follows with a discussion on the importance of situational contexts and introduces the concept of *disruptive contexts*. Different types of physical contexts, e.g. a user's level of physical activity and environment distractions, are explored with emphasis on how these will disrupt existing user cognitive capability in tasks such as forming of perception on on-line material.

The use of context is then discussed in conjunction with Context-Aware Recommender Systems. While user contexts including affective state and other situational contexts have been utilised within recommender systems, none thus far have investigated cognitive capability as a precursor to the actual recommending process. Chapter two concludes by discussing the use of smart-phone sensors, existing research implementation and their potential in real-time recognition of user and environment contextual phenomena.

Chapter three - introduces the Research Methodology used within this study. It discusses the benefits and potential limitation of the quantitative approach followed which relies upon purposive sampling, a non-probabilistic, random sampling method. As this research utilised survey questionnaires in the

form of self-administered questionnaires chapter three discusses the typical considerations that need to be addressed to ensure best practice is followed.

The approach to the sampling of data, i.e. the targeted population, the sample sizes and the issues that arise by using the purposive sampling approach are discussed as are the issues of reliability and validity of data. More importantly, are the details of the steps taken to mitigate typical issues that can arise using quantitative methodologies within research. Ethical considerations are also discussed together with descriptions of the approach taken in the different methods of deploying the survey questionnaires used in the experimentations.

Chapter three continues this discussion by presenting the instrumentation used to collect each of the different sets of data required to conduct this research. Drawing upon the previous chapter's conclusions, specific measurement tools for capturing user feedback are utilized in capturing important user cognitive and behavioural contexts. These include the measurement of affective state, measures of product involvement and purchase-decision involvement, and the measurement of user perception. Also presented is the novel *disruptive situational context questionnaire* which was developed for the purpose of this research.

Chapter four - outlines the approach in the implementation of the survey questionnaires detailed in chapter three. Seven experiments were conducted over four cycles of research which iteratively built upon previous findings together with refinement of the research approach. The survey formats included paper-based questionnaires, on-line surveys using Google Forms and implementations of bespoke Android applications.

Each of the seven experiments are fully described outlining the construction of each survey, i.e. the order in which the questionnaires are presented to the participant, and the method of implementation i.e. paper-based or Android application. Also within this chapter further development of the disruptive contexts questionnaire is achieved as its focus develops to support each specific experimentation's needs.

Chapter four also provides full details of the development of the machine learning processes implemented for classifying different environment and user contexts captured using on-board phone sensors. Neural network pattern recognition tools were used to classify specific disruptive contexts to facilitate prediction of user levels of perception and purchase-decision involvement.

The initial test experiments are implemented using routines developed in Java and Weka data mining libraries. The process of using supervised training for feature data set pattern recognition and the results achieved are detailed in chapter four. The trained inferred function is then implemented within an Android application which is detailed within the final experiment.

Chapter five - describes the Analysis and the Results obtained from the series of quantitative studies completed as part of this research. Each experiment is presented in chronological order following the same structure presented in chapter four. Analysis of experimental results are preceded by the presentation of the data sample statistics and the hypotheses that the experiment attempts to address. Analysis follows each set of results acknowledging not only significant results but also limitations which together are used to shape the development of hypotheses and subsequent experimentations. As work progresses a number of important findings were discovered. Not only does the type of user device, i.e. static or mobile device, impact upon the user's behaviour but so does the immediate environment in the form of disruptive contexts which essentially impact upon our cognitive behaviour. Results also present further evidence that user dominance is a key component that should not be ignored when developing e-commerce systems especially for mobile devise users.

The final experiment in chapter five is a consolidation of three research threads, i) perception of information presented via a mobile device, ii) formation of purchase-decision involvement for high involvement products and iii) an initial exploration of using on-board mobile sensors and machine learning for classifying user-subjective situational contexts. While the author acknowledges limitation within the approach, the results are positive and merit further research into developing the model for commercial use.

Chapter six - presents a discussion which provides an in-depth evaluation of the research completed. The discussion focusses on providing insights into the results achieved using comparisons with previous research outputs and observations of current practices to gauge their impact. An initial summary is presented outlining the research findings which argue that a sound platform has been produced which enable further development of a disruptive context model for use within m-commerce systems. Details of the implications of the results and their effect upon different areas are then discussed. The main focus of the discussion is the importance of user dominance within a mobile context and the influence that disruptive contexts have upon user cognitive behaviour. Also discussed is the implementation of the context-aware model developed, including the opportunities for furthering its development and also the impact that this approach could have on a number of existing research issues.

This chapter also reviews the benefits and limitations of the methodology used together with a number of observations that can be used to guide future research within this area of context-aware m-commerce.

Chapter seven - considers the strengths of the thesis in respect to the requirements of a PhD. The thesis is concluded through the summarisation of the argument put forward and the consideration of the experiments conducted in demonstrating the hypotheses developed. A summary of contributions is also presented and in doing so, this chapter situates the work within a wider e-commerce context with a user cognitive-environment situational focus. Before concluding, this chapter also recommends a number of areas where further work would benefit research.

1.7   Chapter Summary

This chapter has introduced the background to the problem this study attempts to address; encompassing areas of user affective state, cognitive capabilities and situational conditions all within an e-commerce context. From this the primary problems and establish the motivation that drives this work are identified. Objectives are then defined together with an outline of research hypotheses that are followed throughout this thesis.

Following this, the chapter then outlines the research methodology together with a description of the instruments used in the implementation of this research. To emphasize the significance of the work completed for the requirements of a PhD an outline of the contributions are presented. Finally to support the reader's navigation a brief outline has been provided for each of the following chapters in this thesis.

The following chapter presents a comprehensive literature review that situates the work within a wider e-commerce context with a user cognitive-environment context focus. It presents, in further detail, the underlying research problems that exist and develops the hypotheses, detailed in section 1.3, used in tackling a novel advancement for the use of contextual information within the field of recommender systems and m-commerce.

2. Research Setting and Design Motivation

2.1 Introduction

This research considers issues associated with the areas of context, context-awareness and the modelling of affective behaviour, specifically behaviours related to consumer engagement when purchasing products online. The focus of this research is to increase the knowledge of these phenomena and apply the resulting advancements within the field of Context-aware Recommender Systems and mobile commerce.

This chapter situates this work within the theories of Dimensional Models of Emotion, Consumer Behaviour, User Involvement and User Perception of information presented via on-line product placement. In particular the research looks at models including Mehrabian's (1996) three dimensional model of Pleasure, Arousal, Dominance in order to identify a method of capturing a concatenated reading of user affective phenomena (e.g. emotions, mood etc.) suitable for computer systems. Also investigated are aspects of user engagement including decision processes associated with purchasing a product i.e. Purchase-Decision Involvement (Mittal, 1989). Further to decision involvement a discussion is presented on both user perception and user *attitude towards the advert,* which focuses on the likelihood of an advert's success (Lutz et al., 1983). These theories together provide well recognized techniques that can be used to inform an insight into consumer engagement with product appeals.

The challenge involves Context-aware Recommender Systems (CARS). While CARS are fairly well developed in using contexts to inform a system's decision for making recommendations, the general focus is upon relatively simplistic models that do not take into consideration the user's cognitive capacity. Due to the variability of the mobile user's situation this is an unaddressed challenge within the area of m-commerce recommender systems and product placement. While a particular user can be identified as being favourable towards a number of products, if their situation means that they are unable to process the product information, for whatever reason, the product placement will not be successful. This is an issue for businesses that are paying for their advertisements online especially

where competition is high for placing popular, high cost products. If a recommender system can identify a user's level of engagement then this can be used to an advantage by either determining whether or not to place a particular advertisement at a certain time or by changing the style of advert to suit the user's cognitive capacity at the time.

Implementing a context-aware recommender system that utilises both user and environmental contexts to demonstrate effects to user engagement provides the following challenges. While many situational contexts are already in use, which of these can be considered to be detrimental or positive to the situation? Contexts of user mood and emotions are widely associated with consumer behaviours, as are some aspects of the user's physical contexts, including location, company of others etc. This research focusses on these contextual areas to determine relationships which can be used to show indicators of potential user engagement within different situations. In addition to the above, to build a functioning system, appropriate measures to gauge these contexts need to be identified as will the identification of appropriate measures of user behaviour within a mobile system that focuses on product placement.

The challenge is also considered from a technical perspective. Mobile devices, especially smart-phones, are now able to draw upon a wide-ranging suite of 'sensors' to capture valuable contextual data to inform systems of situations and user behaviour. Also discussed are built in sensors (e.g. microphone and accelerometer) and applications (e.g. texting and call functions) with a primary focus upon discovery of user behaviour and their environments. Also considered is the cost of processing sensor data and the need for careful power management.

Section 2.2 begins with an introduction to Affective phenomena, initially identifying the core components involved, i.e. mood, emotions and personality, and then provides a brief outline of definitions and theories. Section 2.3 continues this discussion by discussing in more depth the two main methods for modelling of Affect, i.e. Appraisal and Dimensional theories with particular emphasis on examples of implementation within a computational context.

The chapter continues by discussing relationships between affective and purchasing behaviours. Section 2.4.1 introduces key advertisement techniques and how consumer behaviour is influenced by the content of the adverts by primarily focusing upon opposing presentation styles that leverage different user traits. Section 2.4.2 details the effect of user mood and emotions upon behaviours with a particular emphasis upon cognitive capacity, i.e. the effort that the processing of an advert's content takes.

Section 2.5 continues the chapter by introducing methods of measurement of different cognitive processes that are useful in the assessment of user engagement. Section 2.5.1 introduces Product Involvement and Purchase-Decision Involvement in order to understand how important specific products and services are to a user but also to assess their cognitive capability in making decisions regarding the purchase of these. Section 2.5.2 follows this by discussing user attitudes to adverts and details a measure of perception which this research uses to capture a general attitude towards online material.

Following the above discussion, the chapter continues by introducing the concepts of context and context-awareness in section 2.6.1. Section 2.6.2 then continues by defining the importance of the influence of physical contexts upon both user emotions and thus behaviour. From this discussion evolves the concept of disruptive contexts which proves to be a key contribution to this research.

Section 2.7.1 continues by introducing context-aware recommender systems. The section covers the core concepts and then follows with a discussion on the added depth in functionality that the inclusion of contexts provide the basic recommender processes. Section 2.7.2 continues this by discussing further the use of context for personalizing recommender systems. The use of physical contexts and affective phenomena for improving recommender systems results are discussed in order to outline the benefits of such systems.

Having discussed the benefits of the utilisation of contexts within user interfacing systems, section 2.8 discusses the use of in built smart-phone sensors to capture a wide range of contextual information,

ranging from location through to mood. Concluding the chapter, section 2.9 provides a brief summary before introducing the next chapter.

2.2   Introduction to Affective Phenomena

Affective phenomena (personality, mood, emotions) are not only difficult to measure and predict but there is also little overall consensus as to what they represent, how they are derived, or what influence they have on our behaviour (Picard, 2003). Also needed to be taken into account is that affective phenomena are multifaceted, encompassing emotion, feeling, mood, temperament (emotional traits), as well as being directly associated to our universal personality traits.

Personality traits reflect enduring patterns of thoughts, feelings and behaviour that change little over a lifecycle (Almlund et al., 2011), and when considered alongside user temperament are the foundation that directly influences how our moods and emotions evolve over shorter periods of time (Gebhard, 2005 & Kwek, 2004). Research into these characteristics has produced relatively sound methods of measuring and modelling underlying personality to provide a starting point for establishing other affective phenomena (Gebhard, 2005). These primarily revolve around psychometric testing which has over the years established many theories such as Cattell's sixteen personality factors model (Cattell, 1989) and the very popular model of the Big Five personality traits otherwise known as the Five Factor Model which utilises a comprehensive questionnaire to capture user's Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism (Digman, 1990). Though psychometric testing is the norm, recent studies by Chittaranjan et al., (2011) have shown that it is possible to automatically infer personality traits through smart-phone sensor data modelling.

The areas of psychology and philosophy have also provided multiple theories on the definition of emotion and its associated behaviours, ranging from the Darwinesque evolutionary theories that favour natural-selection (Darwin, 1872), physiological responses (James, 1884) and response to experience (Schachter, S., & Singer, 1962), cognitive theories that advocate a process of cognition – physiological change – action (Lazarus, 1991), and finally dimensional theories that differentiate emotions within a multi-dimensional space (James A Russell & Mehrabian, 1977). Though widely

used in every-day life, the meaning of emotion is widely contested within the cognitive/psychology research community with many apparently informed theories available on what constitutes emotion, and how emotions are formed and communicated (James A Russell, 2003). Confusingly not every language contains a word for emotion (James A Russell, 1991) so even through its use as a label we can be immediately misdirected. This issue could be a contributor towards differences between our common-sense interpretations of emotion and the technical definitions within computational models of emotion research (James A Russell, 2003). Feelings are subjective yet are often used synonymously for describing emotions; this misuse is a common issue that misdirects many research efforts (Klaus R Scherer, 2005). Russell's (2003) definition of Core Affect and its use as a simplistic, always available feeling that is evident within moods and emotions is endorsed in that it is generally understood that at any point in time we can always say how we feel (Yik, Russell, & Steiger, 2011). As with other affective phenomena, emotion is often regarded as an inherited ancestral *folk theory* (James A Russell, 1991) and not a scientific concept, however, primary (basic) emotions do act as primitives for many computational models of affect (James A Russell, 2003). Different approaches have attempted to establish varying levels of granularity including discrete categories of emotion such as love, hate, fear, etc., the coarser categories of positive and negative emotions, and as hierarchy of primary (basic), secondary (complex) emotions.

Regarded as our most basic emotions, primary emotions are often described as being innate, supporting reactive responses such as triggering 'fight-or-flight' behaviours (Becker-Asano & Wachsmuth, 2010). Becker-Asano et al. (2010) go on to define secondary emotions as being complex, arising from a preferential focused cognitive evaluation of outcomes and expectations, however they only tentatively agree with (El-Nasr et al., 2003) that these emotions are based on learned characteristics through the retrieval of memories of events and experience. Whereas personality is relatively resistant to change, emotion is by comparison a fleeting event that interrupts and redirects behaviour (H. a Simon, 1967), and is typically controlled through cognitive content against an intentional object (James A Russell, 2003). Such complex concepts have led to some research seeking

to define object free emotional processes and thus free from cognitive structure (Oatley & Johnson-Laird, 1987). These however, do not lead to a definitive opinion on emotion.

Though mood is relatively understated when compared to emotion (Wilhelm & Schoebi, 2007) it is still dynamic, albeit taking longer periods over which to change and with a greater influence on cognitive processes (Gebhard, 2005). Though a somewhat stable timeframe may facilitate the prospect of real-time analysis it does not detract from the difficulty and the intrusive self-report methods generally used in analysis (Ma et al., 2012), thus, unobtrusive methods for data capture is an emerging trend of research especially with recent advances in mobile technology. So, as a state, mood will last longer than emotion and therefore will be usually less intense in nature and less likely to be derived from a specific event or stimulus (Thayer, 1990). There is however some uncertainty as to the relationship between mood and behaviour. Zimmermann et al., (2003) state that people may not even be aware of their mood until attention is drawn to it even though it is affecting memory, judgment and opinions. Wilhelm & Schoebi (2007) affirm that mood has a subtle effect on 'experience, cognition and behaviour' whereas Scherer (2005) declares that mood neither prepares actions nor interrupts current behaviour. Though disagreement is typical, Mehrabian's (1996) definition of temperament as an average of a person's emotional states captures a consensus. Gebhard (2005) utilises this average of emotions to define a model for mood. Similarly Becker et al., (2006) states that emotions are a mood-changing factor that fortifies or alleviates mood, and that this notion is essential in modelling human-like behaviour. With this understanding it is possible to start identifying the structure of affective-behaviour relationships.

Approaches to measuring emotion and mood differ significantly, utilising physiological-behavioural and psychometric attributes respectively. These methods both offer significant insight, however there is limited understanding as to their integration both theoretically and practically. Though there may not necessarily be a full consensus on what constitutes the different affective phenomena and how they are related to be able to create an irrefutable model, it can be seen from the above that there is reasonable understanding, enough that is for a number of progressive computational models to have been developed.

2.3 Models of Affect within Computing Systems

Affective computing as coined by Rosalind Picard in 1997 has been accepted as the 'label' for computing that 'relates to, arises from or influences emotion and other affective phenomena'. Unfortunately though, extensive research over several disciplines has not provided a consensus for modelling emotion (Scherer et al., 2010). Gunes & Schuller (2012), also highlight that *affect analysis* is often detached from *affect generation* with most practical efforts seeming to focus on one or the other. Therefore it seems unsurprising that underlying psychology theories have not overly influenced affective computing due to skepticism within the computer science and Artificial Intelligence research communities. However, affective computing and fundamental emotional theory cannot be completely divorced without having considerable limitations for progressing this area (Calvo et al., 2010).

Affective computing techniques currently revolve around several popular theories of modelling Affect, with the two main approaches being Appraisal theories and Dimensional theories. Many applications utilising models of affect have been developed to forward the concept of the *virtual human*, simulating the character(s), their affective states and the situations that can arise within a virtual environment. These generally require a process of, the situation assessment, the generation of emotions and the representation of emotional response i.e. scripted voice, gestures and facial expressions. Marsella et al., (2010) suggest that Appraisal theories are both abundant and predominant as they focus on the cause of the emotion with a set of appraisal rules producing specific emotion labels. This focus is obviously acceptable where the environment-situation is fully understood and controlled.

Appraisal theories differ from other emotion theories in that they embrace the notion that it is a person interpreting a situation rather than the situation itself which triggers the emotion (Ortony, Clore, & Collins, 1988). This is beneficial to modellers that have a grasp on attributes and the necessary knowledge to be able to accurately describe a particular character's personality to fit the specific models objective. However, this has limitations, e.g. the system aligned for producing a realistic interactive experience in a learning environment will not consider extreme issues such as a natural

disaster, so is therefore, though fit for purpose, essentially incomplete. Though succinctly argued and applied successfully in many application examples, ultimately Appraisal theories cannot provide fully described and unique situational representations as required within everyday life. Gratch et al., (2009), criticise Appraisal theories as being 'at best' high-level specifications that force assumptions on system representation and processes with often inconsistent and in some cases contradictory predictions of emotional response intensities. To summarise, Appraisal approaches unfortunately appear to be somewhat limited to environment-character simulations and follow the notion that relationships between events, beliefs, desires and intentions are what cause emotion (Lazarus, 1991), thus, without a fully defined 'environment' where goals, events and associations are clearly and accurately mapped out, such as in a simulation, continuous appraisal would not be achievable to the level necessary to accurately produce emotional output. Further to this Calvo et al., (2010) present a number of issues raised in other research, that appraisal theories cannot currently define the minimal number of criteria to differentiate emotions or assess whether cognitive approaches include social functions or even simple emotional reactions such as fight-or-flight.

Making comparisons between computational models is complex (Gratch et al., 2009), however whereas Appraisal theory based models associate behaviours with (usually) a large number of appraisals, dimensional models employ far fewer measurements (Marsella et al., 2010). So rather than attempting to fully describe situational events that someone could be exposed to, or label the complex emotion generated signals in response (Gunes et al., 2011), other popular research has applied models linked to dimensional theories that focus on affect structure and temporal aspects with only a limited attention to cause. Dimensional models conceptualise affective phenomena as points within a two, three or even four and five dimensional space (Gunes & Schuller, 2012), and thus offer an open space within which to map continuous values (Gilroy et al., 2009). By also de-emphasising emotion there is an emphasised focus upon other concepts such as mood and core-affect (Marsella et al., 2010), in other words an averaged representation of life situations (Gebhard, 2005).

Though a number of two-dimensional models have been developed over the past decade or so, they have more recently been rejected as insufficient for describing affect, especially as popular three-

dimensional models cannot be reduced down to two-dimension models (Schimmack & Grob, 2000). Wilhelm & Schoebi, (2007), reference multiple studies that present evidence for three-dimensional models that have been used for both modelling emotion and mood. They also present their own three basic dimensions of mood, namely, *valence*, *calmness* and energetic *arousal*, which, as with most mood evaluation, utilises regular psychometric testing, in this case through measurement of variance and covariance of six bipolar items: tired–awake, content–discontent, agitated–calm, full of energy–without energy, unwell–well, relaxed–tense. There is little evidence showing examples of non-invasive methods of behavioural measurement, i.e. voice, gait and posture, that have been used explicitly to monitor mood, rather they have been primarily applied to measuring short term emotional episodes due to their higher intensity and physical response characteristics (Zimmermann, et al., 2003).

Figure 1: Three Faces of Emotion: A Representation of the
Pleasure-Arousal-Dominance Emotional State Model (Mehrabian, 1996)

Mehrabian's (1996) Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness (PAD), Figure 1, is a predominant dimensional model which has been shown as an effective method of modelling affective phenomena without relying upon discrete labels (Marsella et al., 2010). Rather than focusing on discrete entities such as anger, sadness, joy etc., the method averages an individual's emotional states to conceptualise affective phenomena as a point within a three dimensional space (Mehrabian, 1996). Though a seemingly insufficient level of description, this offers a richer, continuous representation of a user's experience, and, with almost orthogonal dimensions, it has been

possible to achieve affective state interpretation through fusion of separate physiological signals (multimodal fusion) in response to emotional changes over time (Gilroy et al., 2011).

McBreen & Jack (2001) has also shown a reliable method to map the Big Five personality traits into PAD space, this is essential for providing a start value for the evaluation of steady changes in medium term affect (i.e. mood) as well as a control or filter for other affective phenomena (Gebhard, 2005). Once a start point is established then erratic, short-term affective signals, such as emotions, are used, either singly or grouped to produce stronger results, to smoothly 'pull-push' the PAD point (affect point), around the three-dimensional space (Gilroy et al., 2009). This affect point could potentially represent mood, however just utilising emotions as being the control of mood is possibly too lean a method for modelling mood effectively (Gebhard, 2005). Moturu et al. (Moturu, Khayal, Aharony, Pan, & Pentland, 2011) state there are obviously other mood changing conditions that have an impact, such as quantity of sleep or hunger, however it can be argued that the effect of these will influence emotions and therefore our mood if the above premise is followed.

Emotions, both primary and secondary, can potentially be characterised within a three-dimensional space, however, as their fortifying or alleviating effect is short lived (Becker & Wachsmuth, 2006) the 'mood' returns to a baseline over time in absence of, or through the decay in intensity of stimuli (Gebhard, 2005). Following this method has allowed for a model to develop where emotions contribute towards medium-term and long-term processes, such as decision making and motivation, without direct control over long-term behavioural changes, therefore supporting believable, natural behaviour modelling (Gebhard, 2005). Ma et al., (2012) however do highlight the difficulty in reflecting mood swings through analysis of both real-time and historic data due to its subjective nature. Phenomena such as these mood disorders are often discounted when modelling, probably due to their chaotic effect.

Like appraisal approaches, the dimensional model of emotion, e.g. PAD, has been shown to be effective in a variety of applications required to model affect. Becker-Asano et al., (2010) utilises PAD theory to simulate primary emotions as well as three prospect based secondary emotions, as does

(Gebhard, 2005) who represents mood in addition to a set of twenty four emotion types within a virtual environment. So, efforts to map discrete emotions into a dimensional PAD space have shown varying levels of success with a global mapping still outstanding. Though Hoffmann et al., (2012) determine that this will possibly only be achieved using an individually calibrated model, this does not defer the value of dimensional theories where discrete labelling is not essential. PAD and other dimensional theories have also been used effectively to model live user data, examples include *speech* (Gilroy et al., 2009), (Gunes & Schuller, 2012), (Kipp & Martin, 2009), *head and upper body motion* via video (Gilroy et al., 2008), (Gilroy et al., 2009), (Lance et al., 2007), (Espinosa et al., 2010) and *physiological*, e.g. EMG /EEG data, (Gilroy et al., 2011). Though there are many more examples where different physiological and behavioural features have been used to determine emotion they generally do not then explore further the modelling of affect and map onto an affective model such as PAD space to create a more complete model. This research follows this convention and adopts Mehrabian's three-dimensional PAD model of user affect within the research conducted herein.

2.4   Affective-Purchasing Behaviour

The main focus of this research is to provide a greater understanding of the influence that situational contexts have on user behaviour towards product placements via m-commerce. Factors such as product characteristics are obviously critical to the success of consumer-product engagement, however an understanding of exogenous factors e.g. time pressure, lack of mobility, geographical distance, need for special items and attractiveness of alternatives are needed to fully understand consumer motivations for purchasing online (Monsuwé, Dellaert, & Ruyter, 2004). Different affective phenomena can also influence different purchaser traits including, motivation (Rohm and Swaminathan, 2004; Smith and Sparks, 2009), impulse buying (Youn & Faber, 2000), compulsive buying (Otero-López & Villardefrancos Pol, 2013), brand attitude and ad-claim recall (Myers & Sar, 2015), risk-taking and self-image (Brave & Nass, 2002).

The following sections introduce the concepts of consumer behaviour towards different types of advertisements and how user emotions and moods (affect) can be used to determine how these

behaviours are formed. The concept of disruptive situational contexts is then introduced and how they should also be considered in terms of their impact on user behaviour when a user is forming perceptions of mobile data.

2.4.1 Consumer Behaviour and Advertisement Techniques

Though an everyday occurrence, the act of purchasing an item, whether in store or on-line, is a complex process that includes both environmental factors and consumer characteristics, marketing and environment stimuli, motivation and personality factors. There are many drivers that form an individual's approach to the purchasing cycle. These complex emotional drivers include social potency and closeness, stress reaction, control, harm avoidance, traditionalism, and absorption (Youn & Faber, 2000), enjoyment (Yang & Kim, 2012), and perception of risk (Bhatnagar, Misra, & Rao, 2000). These in turn influence purchasing behaviours of impulse (Youn & Faber, 2000), a need for convenience and information search (Holmes et al., 2014). Personality traits generally form our emotional responses to situations so are key to understanding particular purchasing behaviours such as an unplanned event that is made through a 'snap' judgment process i.e. impulse buying (Youn & Faber, 2000).

Some purchasing behaviours, e.g. impulse buying, review stimuli to form a quick, convenient representation of a situation. It is often characterized as a type of holistic processing that has advantages of speed and reduced cognitive effort (Burroughs, 1996). A typical example of a holistic processing technique is mental imagery. This is an influential tool for advertisers for enhancing brand attitudes while engaging consumers (Myers & Sar, 2015). The process not only includes the marketing message cues of visual, auditory, tactile and emotional (Suinn, 1990), but also draws upon the purchaser's previous experience, memories and daydreams to fully form a visual image of the situation (Holmes et al., 2014). This contrasts with analytical processing which forms a comprehensive understanding of a situation through analysis of individual stimulus characteristics. Burroughs (Burroughs, 1996), determines that the style of processing is selected depending on the characteristics of task, stimulus and the individual consumer.

An individual's purchase behaviour can be predicted through their perception of risk, and a consumer will avoid impulse buying when perception of risk is high (Lee, 2008). Bhatnagar et al., (2000) report on relationships between risk, convenience and on-line shopping, stating that certain product categories, e.g. music and CDs, are not generally considered risky. This is because of the practicalities of shopping on-line, i.e. reduction of costs and an increase in convenience to make purchases more likely (Bhatnagar et al., 2000). Products with higher value are perceived 'to have' or 'as having' a higher risk, however they could be viewed as being more convenient to be purchased on-line if more involved (Bhatnagar et al., 2000), or are likely to require an evaluation process or other pre-purchase activity (Holmes et al., 2014).

Evaluation processes used in information search rely upon analytical information processing to produce a comprehensive understanding (Burroughs, 1996). Information search via the use of mobile phones is important in the evaluation of alternatives and pre-purchasing activities, e.g. finding discount vouchers (Holmes et al., 2014). Using an analytical processing style the individual will attempt to understand details of the purchasing situation from all angles. In doing so they will be more likely to identify all important information including negative factors and therefore be able to limit risky consequences (Burroughs, 1996).

In addition to considering styles of information processing, risk acceptance and levels of processing effort we should also understand how common techniques for manipulating emotions are important in marketing campaigns. I have briefly mentioned emotional drivers that shape our decisions and behaviour. The use of emotional appeals in marketing create a psychological reaction that could be resolved by acting upon the appeal message, e.g. through purchasing an item (Hastings et al., 2004). Fear appeal has been widely used in commerce and awareness campaigns with varied success depending on content and severity of message (Hastings et al., 2004), however the basic premise is to focus on insecurity and concerns in order to prompt action. Positive appeals also exist and are written to engage arouse emotions like love, desire or humour to invoke behaviours including self-esteem (Robberson & Rogers, 2006).

While the use of different advertisement techniques can leverage different user traits and influence purchasing behaviour, the advertiser should not overlook the effect that user emotions, mood etc. have upon behaviour. In other words a different underlying mood can affect the effectiveness of a product placement. The next section (2.4.2) discusses the relationship between consumer behaviour and affective phenomena.

2.4.2   The Influence of User Affect upon Consumer Behaviour

Myers & Sar, (2015) discuss the relevance of mood and its likelihood as a context for an advertisement to be successful. Alongside previous research efforts they state that their findings appear to show that positive evaluation of an advert is enhanced when in a positive mood through the increased ability to undertake mental imagery processing. They also suggest that capacity to evaluate detailed information is reduced during periods of positive mood but this then increases during periods of negative mood. This is supported by Escalas, (2004), who notes that the effort in generating the mental imagery decreases the ability to undertake further cognitive tasks such as critically analyse the adverts' content which could in turn produce more negative evaluations.

These findings suggest that mood is a useful context when ascertaining how to present items via a recommender system. The use of mental imagery may act to make the recommendation more appealing as mood positivity increases and thus is conducive to the actual success of the advert. Where a negative mood is present and mental imagery deemed less favourable, then recommender messages that provide detail suited to analytical processing could be more successful.

Previous research has also determined the effect of mood on our perception of risk. Lee, (2008), presents results which demonstrate that elements of positive mood are related to impulsive buying traits. Brave & Nass, (2002) state that it is expected we will endeavour to maintain a positive sensation by being more risk averse with engagement likely to continue with low-risk impulse sales. In addition to this, when in a negative state we are generally aiming to recapture a more positive outlook and are more likely to engage with riskier purchases to kick-start the positive emotional process (Brave & Nass, 2002).

Research has often reported that when we are in a positive mood and are presented with a hypothetical situation we are more risk favourable. For example Yuen and Lee (2003), note that those in a positive mood are less conservative and more open to risk. However they do report significant differences of the effect of mood on levels of risk acceptance. This could be explained by noting Isen, (2000), who suggests that when a person is presented with a real risk situation they are more likely to be risk adverse. Other research such as (Church, Hoggan, & Oliver, 2010) postulate that negative mood is more complex than basic categories of laboratory induced moods of 'sad' as used by (Yuen & Lee, 2003). It may therefore also be logical to suggest that real life situational mood and emotions may potentially produce different results to laboratory findings, especially under different situational contexts.

An interesting consideration for the use of mobile devices is the presentation of information in an accessible, intelligent manner. The size of device and our general preference for convenience should influence the way information is presented. Large sections of text may be off putting to a user, or indeed be preferred, depending on their mood or other situational context. Martin, (2003) reviewed several research efforts. He summarises that happy moods lean towards a shallower, heuristic processing due to a lowered cognitive capacity e.g. probably through being distracted or when in a pleasant environment. Whereas sad moods suffer more effortful processing potentially due to a more problematic environment.

The use of positive and negative messaging in adverts and other action appeals have been widely discussed and used in both industry and public sectors for decades. Simple optimistic appeals to traits, such as self-esteem (Robberson & Rogers, 2006), are commonplace and provide positive messages to encourage actions that will produce a positive outcome. Fear appeals are a different technique which are more complex and require a greater understanding of how negative thoughts are transferred to the user in order to promote an action (Gardner, 1985). A prime example of a use for fear appeal is the health awareness warning focusing on long term change; see review by (Lottridge, Chignell, & Jovicic, 2011). Mood has also been shown to have an effect on both positive and fear appeals. Wegener et al., (1994) observed that someone in a positive mood would be persuaded more by a

positively framed message than would a person in a negative mood. They also found that the opposite occurred for negatively worded messages, with those in a negative mood being more susceptible to fear appeals.

The previous sections have introduced affective phenomena and its relationship with consumer behaviour. To aid the development of a context-aware framework that considers the relationship between user affect, consumer behaviour and the physical environment the following sections investigate the concepts of Purchase-Decision Involvement and User Perception as tools for gaining further insight into these phenomena.

2.5   User Involvement and Perception

2.5.1   Measurement of User Purchase-Decision Involvement

Product Involvement is a relatively well understood concept that provides insight into how consumers engage with products, brands and the general advertisement process. Product involvement is reliant on constructs that make up the purchaser-product relationship. These include personal preferences and perceptions, as summarised by (H. S. Kim, 2005), influencers of buying choice (Yeh & Lin, 2010) and manipulation of product perception (Laurent & Kapferer, 1985). Product involvement is considered as a layered concept most commonly separated into *enduring involvement* and *situational involvement* as first coined by Houston & Rothschild, (1977). The concept of enduring product involvement is simply a person's level of involvement that is always present. This may be static or may slowly change as taste, behaviour and other personally related contexts develop over time. Parallel to enduring involvement it is said that we also are subject to situational involvement, fundamentally the setting in which the product will be consumed (Laurent & Kapferer, 1985).

It is obviously difficult to determine situational product involvement from user behaviour without explicitly asking. It does however seem more plausible to establish a general understanding of enduring, or indeed an element of both enduring and situational involvement through the analysis of behaviours such as knowledge acquisition via search and other on-line activities. This is particularly true with the mobile device which is becoming ever more entrenched in the product purchase cycle. It

therefore seems reasonable to agree with Kim, (2005) that methods of product involvement measurement such as those developed by Laurent & Kapferer, (1985) are suitable for broader analysis of product involvement for achieving results that are sought in this research.

Research into consumer product involvement has generated a considerable amount of research findings, including a number of measurement tools focusing on widening knowledge of the product-user relationships. The most cited examples include the Consumer Involvement Profile (Kapferer, Laurent, & Hec, 1993), and the Personal Involvement Inventory (Zaichkowsky, 1985). While still considered key to our understanding of product involvement these models have received criticism and revision, in the case of Personal Involvement Inventory by the author's own hand (Zaichkowsky, 1994). Most noteworthy in their assessment of these tools are Mittal, (1989) and Mittal & Lee, (1989) who identify that only one of the four Consumer Involvement Profile facets are real measures of involvement with the other three being antecedents which shape in part the development of the purchaser's involvement. These concepts formed Mittal's, (1989) development of the Purchase-Decision Involvement measurement tool which has been likened by Michaelidou et al., (2008) to situational involvement.

The development of Purchase-Decision Involvement (PDI) (Mittal, 1989) was to demonstrate the difference between product involvement and the decision process associated with purchasing a product. In doing so PDI is defined as a nonresponsive state of mind that identifies the benefit of a specific product purchase, reiterating the distinction between 1) enduring and 2) situational involvement and 3) responsive behaviours that manifest themselves in the decision making process. Adopting the term PDI as opposed to situational involvement enables researchers to imply with clarity that a decision process is in place which is governed by the consumer's motivation (Mittal, 1989).

Through the understanding of a user's level of involvement, a system can enhance the method of persuasion an m-commerce recommender system or embedded advertisement message utilises, and therefore influence how a person will respond. Park et al., (2008a) suggest that high involvement requires cognition, reasoning and comprehension whereas low involvement is only a routine

behaviour choice, relying on product experience and peripheral cues such as size and colour of the advert. Processes including behaviour and the evaluative aspects of cognition have been shown to be affected by different environment contexts (Guski et al., 1999).

2.5.2   Measurement of User Perception

Liu et al., (2012) observe that researchers and practitioners must understand consumer perception in order to be effective in the area of mobile advertising. Research into context has partly enabled this; however, understanding of mobile user context is still incomplete and is a popular area of research. User perception is fundamental to understanding a user's *attitude towards the advert* (A_{ad}) and thus the likelihood of an advert's success (Lutz et al., 1983). A_{ad} is the positive or negative feelings towards an advertisement, service or product within a particular context and has a strong impact on purchasing (Hadija, Barnes, & Hair, 2012). Concepts of perception and its measurement are complex (Kleinsmith & Bianchi-Berthouze, 2012) and with the measurement of A_{ad} there is also uncertainty. Even early work ascertained that A_{ad}, as a mediating casual variable that influences purchase intention, could follow many possibilities (Lutz et al., 1983). Research attempting to measure A_{ad} has produced multiple measurement scales. Bruner et al., (1995) identifies 46 multi-item measures involving 50 different semantic differentials and conservatively suggests an openness within the field towards measures of A_{ad}.

Therefore drawing upon simple measures used to calculate A_{ad} and through selection of very general semantic differentials which encapsulate the majority of those shown to have been used previously within, Bruner et al., (1995) state that it is possible to opt for a very short and broad measure of attitude to gauge user opinion of advert content. For example *effective-ineffective*, *appealing-unappealing* and *believable-unbelievable* are not content specific and can therefore be used as a tool for forming a measurement of perception of a broad range of advert styles. This measurement of perception is used within our experimentation discussed in chapter three and is discussed in detail below.

Though the term effectiveness is utilised as part of our perception measure its use should not be compared with the term *advertising effectiveness*. Advertising effectiveness is widely understood to be the final measure of an advert where the consumer actually makes a purchase. Research in this area spans decades e.g. (Lavidge & Steiner, 1961), (Mackenzie, Lutz, & Belch, 1986). Attitude towards an advert, or a recommendation, is clearly key towards its success (Mackenzie et al., 1986), thus the use of effective-ineffective is to capture a general measure of the subject's personal perception of whether a message is capable of producing a deep impression or achieving its intended result.

In addition to this the use of believable-unbelievable is to represent the user's perception of the message's credibility, which Lutz et al., (1983) identify as a determinant of advert attitude. The recent world-wide study by (The Nielsen Company, 2013) reports that credibility is a fundamental component towards advert effectiveness. This is consistent with the wider research community's opinion of the impact of trust of mobile advertisements and recommender systems (Liu et al., 2012).

With regards to differential appealing-unappealing, appeal is obviously a personal thing. It is clear that visually appealing adverts accelerate a consumer's intention to purchase (J. Park, Lennon, & Stoel, 2005), however other content is also important. Park et al., (2008b) determine that appeal to emotions will be particularly appropriate to advertisements within the mobile environment. Hadija et al., (2012) note that users of social media do notice embedded advertisements but quickly disregard them to focus on other content such as friend's profiles and pictures. It is clear that this is mostly due to the user's focus on the 'task in hand' but it also identifies that an advertisement must focus on characteristics of attractiveness, design and use of colour to be successfully appealing (Hadija et al., 2012). Therefore it is postulated here that a purchaser's perception of an object's appropriateness and design, i.e. appeal, is critical to understanding likelihood of engagement and success in its objectives. Though simple, the above three semantic differentials provide an aggregate of key elements to retrieve a realistic understanding of user message perception within real-life situations using mobile devices.

Having discussed various user factors, including affective state, cognitive capabilities and behaviours, the following sections introduce the notion of *context*. These user factors are themselves contextual elements that support a profile that supports our understanding of a situation. The following sections introduce context and context-awareness with a focus upon mobile user environments.

2.6 Situational Context

2.6.1 Context and Context-awareness

To be able to explore the area of Context-aware Recommender Systems research needs to establish an understanding of the term *context* and how systems can be defined as being *context-aware*. The term context is multifaceted in nature with no complete unifying definition (Bazire, Bazire, Brézillon, & Brézillon, 2005). Contexts can be static but also dynamic, and they are related to objects, tasks and the people involved. It can therefore be difficult to fully define which situational contexts are relevant, and to what extent (Adomavicius & Tuzhilin, 2015). Due to its importance within numerous areas, context has been studied widely across many research disciplines that span from computer science through to philosophy. Each tend to take the term under their own idiosyncratic view and this has produced many definitions that expand upon the generic Oxford Advanced Learner's dictionary definition of 'the situation in which something happens and that helps you to understand it' (Hornby et al., 2010).

Invariably, applicable computer systems are labelled as being 'context-aware' rather than 'situation-aware' and it is important to understand why this convention exists and whether breaking from convention will impact the acceptance of any proposed model. Put simply, context is the information that supports the characterisation of an entity's situation at a given point in time. Meissen et al., (2005) consider a situation as a snapshot of all contexts on which propositions can be developed. In terms of a computer system, Dey, (2001) states that 'context is about the whole situation' but also acknowledges that relevance is important as not all aspects are essential to all situations. Within computer science and system development, context-awareness is a feature of a system that needs to react to a dynamic environment (Kokar & Endsley, 2012); its use implies that a system uses context to

improve relevance of a service supplied by an application as well as provide patterns that can be used to inform changes in behaviour and/or environment (Mehra, 2012). It has not however been shown to imply expected behaviour to every situation that someone could be exposed to; expectations are normally limited to within a particular domain, service or item. This notion provides both benefits and difficulties: benefits for applications with specific needs, in that development requirements can be focused and costs can be kept to a minimum; difficulties in that this has hindered the development of a complete framework that can be used to develop any fully situational-aware system.

There is still limited understanding of the depth of the contextual profile required to achieve an optimum user-focused context-aware system and though it is unlikely that every domain will require the same level of granularity it is important to identify relevant context from which to develop any context-aware system. Monsuwé et al., (2004) state that a framework is needed to understand the factors that affect consumer attitudes towards online shopping. Early work by Belk (Belk, 1975) discusses consumer behaviour and categorises situational variables as physical and social surroundings, temporal perspective, task definition and antecedent states such as temporary moods or conditions applicable to the consumer. However each person associated with a set of contexts can have a different perception of any of the factors involved (Saucier, Bel-Bahar, & Fernandez, 2007). This highlights the need to model the differences between general consensual knowledge and subjective knowledge of the situation. Block and Block, (1981) produce one such framework through analysis of situational features (contexts) and categorizing all situations into levels of environmental/physical features, canonical/consensual features, and functional/subjective features.

a) *Environmental or physical-biological features* are typically objective and observable elements that are prototypical lending themselves to be observable by machines (Saucier et al., 2007). For example "I am at the cinema in Oxford Street". Typical examples of contexts in this category would include location and environment physical features.

b) *Consensual or canonical features* provide a level of insight into shared or common knowledge that would be applicable to a group of people within the same situation. These features include people and activities and are a secondary layer to the initial environmental

features. For example "We are here to watch a film". They provide cultural and group perceptions but are however less observable to machines (Saucier et al., 2007).

c) *Functional or subjective features* are most salient to the individual and take into account thoughts, opinions, perceptions that relate to behaviour. For example 'I think this film is boring but my wife is loving it'. These contextual factors are obviously very difficult to observe explicitly. However, through the level of personal data that online activities such as social media provide, insight into emotions, traits and behaviours are now more achievable.

Research into situational categorization is primarily limited to areas including psychology, personality and humanities with computer applications solely using the term context. In Adomavicius et al.'s work (2011) context is sorted into four types that impact a mobile service environment. These are physical, social, interaction media, and modal contexts.

a) *Physical:* This category relates to the user and environmental contexts including (to name a few) time, location and activity.

b) *Social*: This category considers the number of people around the specific user and also their interaction with others using an electronic device.

c) *Interaction media:* This category is the information regarding the electronic device in use, for example, mobile phone, and the media being used e.g. text, music, movies etc.

d) *Modal*: The category of modal contexts is the most complex as it ranges from a user's goals, motivations to mood, perceptions and cognitive capabilities (Adomavicius et al., 2011).

The above differs considerably from the Block & Block, (1981) framework with a focus upon key contextual-factors that are associated with the mobile device user. Considering contextual factors within a specific situation, itself a context, clarifies the need and the level of need for individual contexts within a system. So, while being able to categorize aspects of a situation is important for overall understanding, the identification of individual contexts within a narrow situational context makes implementation of context-aware systems more attainable. However as previously mentioned this has also limited the development of the area of recommender systems and addressing this is the

key aim of this research, primarily the implementation of modal aspects to understand user perception and involvement within mobile recommender systems.

This research hypothesises that understanding behaviour towards a set of situational contexts can be utilised to optimise context-aware systems by providing a reasoned reaction towards, not only the presented options, but also the method of presentation to the user. Here it is stipulated that the addition of affective phenomena to the contextual picture is to also consider the user's behaviour as reactional and not just as an additional element of the context that influences preferences.

This research primarily focuses upon the interaction between the physical and modal contexts as laid out by Adomavicius et al., (2011). Section 2.3 has previously discussed how user mood and emotions can affect consumer behaviour; the following section introduces how the relationship between physical contexts and behaviours is influenced.

2.6.2   Influence of Physical Contexts

Typically mobile devices, in particular smart-phones, are small and designed for an on-the-move, multi-tasking lifestyle. Depending on their situation, users may not always have the ability or intention to undertake more demanding or sensitive tasks via their smart device. Therefore they may only engage when in an environment favourable to the task e.g. somewhere quiet to consider the options calmly and securely. Mallat et al., (2009) found that independency of contexts, including time and place, were essential when completing activities using mobile devices. Kaasinen, (2003), identify that there is a high requirement for a system's ease-of-use and ability to adapt to user behaviour. Environmental contexts could not only have an impact on the user's preferences (Adomavicius & Tuzhilin, 2015) but also their ability to process information or make decisions. From the above it is possible to take contextual factors as likely to be key to understanding a user's likelihood of engagement with an advertisement message. This could be an indicator that decision processes become more complex where situations become unfavourable physically and where devices are limited in ability in delivering relevant information at an appropriate time. This premise is followed throughout this research.

The context label 'location' has been used successfully to identify that mobile device users are most likely to undertake consumer behaviours (e.g. information search, review alternatives, purchase) when they are at home (Holmes et al., 2014). However studies are often limited in that they rely on reflection of habits and not a clear picture of the contexts associated with that location. All situations should be regarded as complex and dynamic with a range of contexts that are not static, consistent or necessarily repeatable in nature.

While a user may associate different locations with different emotions (Rachuri et al., 2010), (Ma et al., 2012), or seek particular places to regulate mood (Korpela, 2003), or undertake tasks (Holmes et al., 2014) these are choices selected via experience or habit. As specific moods could be associated with particular locations, it seems probable that contexts that make up each scenario will collaborate to form different outcomes that will then influence the current mood or emotions.

Environmental stressors such as noise and overcrowding can affect both behaviour and the evaluative aspects of cognition (Guski et al., 1999), as do distractions (McGehee, 2014). A person's perceived control within a physical environment has also been shown to be crucial in mediating emotional and behavioural responses (Hui & Bateson, 1991). Therefore where perceived control is reduced or where annoyance is increased then contexts including crowding (Hui & Bateson, 1991), interruptions (Speier et al., 2003) and noise (Banbury & Berry, 2005) could all be implied to have an effect on behaviour by impacting cognitive capacity. Similarly, research into exercise has been regularly shown to improve our cognitive function (Hogan et al., 2013), (Erickson et al., 2015) and has an overall benefit to our well-being and behaviours. It can be suggested that a lack of recent activity could be detrimental thus producing a similar result to negative situational contexts. However contrary to this is that a highly active mobile device user is going to use aspects of their device differently and have different levels of involvement than that of an inactive user. Therefore under alternative situations results associated with activity may present different results to that suggested above. It has also been shown that people prefer to make purchase decisions when based on positive motivation (Hansen, 2005), so where affective state is negative within negative situational contexts it is probable that we are less likely to engage. Thus it is hypothesized here that negative environmental contexts will have a

detrimental effect on decision involvement when we are feeling negative and therefore increase this correlation.

Paulos et al., (2004) show us that our perception of a place is dominated by the people we share it with. Typically within familiar places these tend to be friends, family and colleagues, however even strangers that we repeatedly encounter can become familiar. Familiarity is also a cognitive variable that facilitates performance (Goodman & Leyden, 1991), improves feeling and attitudes (Moreland & Zajonc, 1982) and facilitates trust (Luhmann, 2000).

Building upon the discussion presented above this research utilises familiarity and contextual stressors as components of an *unfavourable physical situation* i.e. where the user is subjected to unfamiliar elements as well as one or more contextual stressors. Thus it is postulated that an *unfavourable physical situation* to affect cognition to such an extent that the correlation between affective state and purchase-decision involvement and/or user perception would become significant. To support this concept the term *disruptive contexts* is introduced to the area of context-aware systems. As described above these are contexts, both user and environmental related, that affect user cognition and therefore a user's ability to engage. Examples focused upon here are user unfamiliarity, e.g. with people and environment, and contextual stressors, e.g. noise and distractions.

Compared to the desktop PC user, the mobile user is subject to more complex, disruptive and inconsistent environments so therefore will require a more complex set of emotions than would be associated with the average user in a controlled, familiar situation. The mobile user will be required to form a greater level of trust of both information presented by the device and the actual environment. They will also be potentially more influenced by traits described by Broekens, (2012), i.e. approach versus avoidance, coping, control, power and influence which in turn suggests that a level of user dominance is involved (Broekens, 2012). Mobile device users are also generally required to process information in a wider range of situations so processing styles may vary depending on surrounding contexts. In other words where levels of positivity determine behaviours for users in relatively controlled environments using suitable devices, i.e. a PC in an office, it is more likely that mobile

device users will rely on additional aspects of their affective state to engage in a decision process, e.g. arousal and dominance.

The above hypotheses prompts us to investigate whether selected situational context can influence the relationships between affective state and purchase-decision involvement and user perception. The result should provide a platform on which to model the management of output for context-aware recommender systems and on-line advertising. The following section introduces context-aware recommender systems and explores methods for implementing such a platform.

2.7   Context-aware Recommender Systems

2.7.1   Modelling and Incorporating Context in Recommender Systems

Recommender systems are typically computer systems used to make suggestions to a user based upon 'consumables' as provided within the domain in which the system is focused. Recommender systems have traditionally focused upon two entities, namely *users* and *items*, with no further consideration for additional contextual information such as time, place or company of others   (Adomavicius & Tuzhilin, 2015). Due to the typically large volume of data found in a recommender dataset, research contributions have primarily focused on the art of filtering items before presenting them to the user. These filtering methods range from *Content* based to *Collaborative* based and of course *Hybrids* of the two main methods. While content filtering systems focus upon user preferences and their interactions with the recommender system, the collaborative filtering system produces recommendations based upon preferences or tastes shown by users with similar characteristics and behaviour as the user receiving the recommendation. Each method has its issues, such as the 'new user problem' and are continuing areas of research.

The use of a recommender system is a predictive problem. A function is used to estimate a rating between a user of the system and the items within the system. Using the user–item ratings that are known, the recommender system will attempt to estimate the ratings not as yet rated to produce suitable suggestions for the user to consider (Adomavicius & Tuzhilin, 2015). For example a movie recommender system will take explicit movie ratings to estimate a recommendation ranking for other

films of the same genre. The user would then be presented with recommendations based upon their previous selections of films using the system. This is a two dimensional approach as additional contexts are not considered, see basic rating function (1):

$$User \times Item \rightarrow Rating \qquad (1)$$

While traditional methods of recommender systems are understood to use user preferences towards a set of items to establish suitable recommendations, context-aware recommender systems attempt to model the user's preference within a limited number of contextual features (Adomavicius et al. 2011). Temporal context in particular has played an important role in improving recommender systems' output in the form of suitable suggestions within a specific circumstance. For example a user may be inclined to search on-line for more personal items during weekends or evenings whereas during working hours search may focus more on general or work related items. In this case the context of 'time' would be the dominant feature.

With the introduction of contextual information the basic rating function is now operable within different conditions making suitable recommendations harder to obtain. For example the user of the movie recommender system may now be with their children and atypical recommendation of films of different genres may be more suitable. With the addition of contextual evidence above the direct user-item relationship the prediction problem becomes multidimensional (2):

$$User \times Item \times Context \rightarrow Rating \qquad (2)$$

Contextual factors, including location or a task's purpose, can be explicitly defined and mapped over time. Adomavicius et al. (2011) describe the importance of time above other contextual factors, stating that contexts can be *static* and time independent, or *dynamic,* i.e., changes in use or structure. These extremes can be either *fully, partially* or *non-observable* ranging from a well-documented situation to a predictive model that requires a high level of latency (Adomavicius et al., 2011); the implications of each category are shown in Figure 2. Having fully observable and static contextual criteria provides information that is stable, delineable and independent of activity which can be

mapped to Dourish's, (2004) 'representational view'. This level of insight can provide an understandable and represented situation on which to produce a model, however the extreme opposite of unobservable and dynamic context where nothing is known about the situation provides a far more uncertain baseline from which to work.

How Contextual Factors Change	Knowledge of the RS about the Contextual Factors		
	Fully Observable	Partially Observable	Unobservable
Static	Everything Known about Context	Partial and Static Context Knowledge	Latent Knowledge of Context
Dynamic	Context Relevance Is Dynamic	Partial and Dynamic Context Knowledge	Nothing Is Known about Context

Figure 2: Contextual Information Dimensions (Adomavicius et al., 2011)

While context-aware recommender systems are typically domain specific it is still difficult to define all relevant contexts (noting that not all contexts will be relevant) as they can be related to the person, the task, the interaction or the situation definition (Bazire et al., 2005). Passive observation and explicit user feedback are used to modify the understanding of dynamic contexts, iteratively refining to produce suitable recommendations. However adding user mobility compounds the complexity of the ranking system used, as requirements for services have to meet the anytime-anywhere criteria that a mobile user demands. Systems also need to be as unobtrusive as possible so they become integrated into everyday use.

Adomavicius et al. (2011) recognise two general categories for implementing contextual information within recommender systems, *contextual preference elicitation and estimation* and *context-driven querying and search*. Where the approach of contextual preference elicitation and estimation attempts to model and learn user preferences through observations of the interactions between users and the system, the context-driven querying and search method uses contextual information to query a repository of resources. This second method is typical of electronic tour guides that recommend points of interest to a user based on best match of resources and the situational context. Obviously systems

can implement both methods, for example the UbiquiTo system (Cheverst et al., 2004) utilises both contextual information but also user preferences and interests.

For the method of contextual preference elicitation and estimation Adomavicius & Tuzhilin (2015) identify that the 2D rating process can take place at different stages of the recommender process. Depending on how the contextual information is most effective, different approaches are used in the form of contextual *pre-filtering*, *contextual post-filtering* and *contextual modelling*; figure 3 represents the three forms that the process can follow.
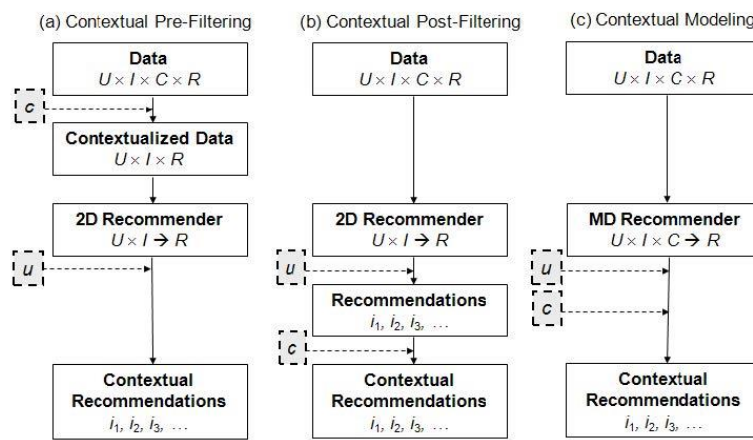
Figure 3: Paradigms for Incorporating Context in Recommender Systems (Adomavicius et al., 2011)

Contextual pre-filtering is where the context is used to select an appropriate set of data that can have the ratings applied using any existing 2D recommender model. This is an obvious advantage, however exact pre-filtering, especially where there are multiple contexts in consideration, can significantly reduce the size of the data set available for the rating algorithm.

Generalised pre-filtering was introduced by (Adomavicius & Tuzhilin, 2005) for producing hierarchical models to establish filtering criteria with reduced specificity. For example while standard pre-filtering could identify context as c = (children, partner, Saturday) as contexts within the movie recommendation system, the generalised filtering method could reduce this down to c = (family, weekend). This would produce a larger yet still focused dataset on which to apply the rating algorithm.

This method of producing localised rating models can outperform traditional 2D techniques, however the pre-filtering and thus reduction of the dataset can produce sparsity within the data and therefore could underperform against an unfiltered process (Adomavicius et al., 2011). There are a number of methods that have been used to overcome the sparsity effect, namely combining a number of pre-filters with a default option of no filtering (Adomavicius & Tuzhilin, 2005). The different approaches to contextual pre-filtering include item splitting techniques, where *copies* of the item are said to be consumed within different contextual criteria (Baltrunas & Ricci, 2009). Baltrunas et al., (2009) defined microprofiling where the user has several profiles (potentially overlapping) that represent the user's behaviour within a particular context. Each micro profile then receives an individual recommendation which can then be used to inform the rating process.

Contextual post-filtering produces recommendations using 2D rating methods before considering any contextual information. It will then use a post-filtering approach to adjust the recommendations initially produced by applying rules based upon the context available. This stage is completed by either adjusting the ranking initially produced or by completely removing the irrelevant recommendations to suit the contexts applied.

There is no documented, conclusive evidence as to whether post or pre filtering produce the best results – it is entirely dependent on the application and the context involved (Adomavicius & Tuzhilin, 2015). Both methods however benefit from the ability to incorporate any 2D recommender technique and thus minimise the complexity of developing a new system. They also benefit from the use of contextual generalisation to minimise the sparsity problem when attempting to produce recommendations on a reduced dataset.

The third method **Contextual modelling** utilises true multidimensional recommender functionality through explicit use of contextual information in determining a prediction of the user's rating (Adomavicius & Tuzhilin, 2015). Contextual modelling has been approached in a number of ways either by extending existing 2D methods using matrix factorisation (Koren, 2008) and tensor factorisation (Karatzoglou, Amatriain, Baltrunas, & Oliver, 2010) or through machine learning

techniques to extend the recommender space through incorporating additional contextual dimensions (Oku, Nakajima, Miyazaki, & Uemura, 2006).

Thus far the main research efforts have focused upon the above methods of implementation of contextual information in an attempt to improve recommender systems' success. Here I am proposing a complementary layer of contextual analysis that will support existing methods of producing actual recommendations. The aim is to use modal and physical contexts to establish a mobile device user's ability to engage with the recommendation that is to be presented. In other words: is the user's situation conducive to their willingness or ability to process the information given? This layer of analysis will complement the existing processes discussed above by determining a potential 'level of engagement' and thus provide insight as to whether to make a particular product placement or not.

2.7.2 Context-aware Personalised Recommendations

Many examples of context-aware recommender systems in existence make use of physical contexts, including time and location. These are generally used to determine the recommendation in terms of logic that would apply to the user activity and likelihood of satisfaction in the choices made available. For example a mobile recommender system for tourism, i.e. an electronic tourist guide, can utilize physical constraints including weather, user disability, timing and budgeting for meals or breaks (Gavalas et al., 2014). Using this information the system could suggest appropriate 'points of interest' (POI) along a route that a user may find of interest within a certain area i.e. a city. If the weather was bad then the user would likely appreciate more immediate POIs that were indoors and thus ensure satisfaction with the recommendations. Other contexts that have been used to help improve the performance of these tourist guides include, but are not limited to, methods of transportation (Saiph Savage et al., 2012), patterns of user mobility (Gavalas & Kenteris, 2011), user mood (Saiph Savage et al., 2012) and social environment (Gavalas & Kenteris, 2011).

Another popular area of research within context-aware recommender systems is film and music recommender systems, with many commercial successes following this research, a famous example being the Netflix Prize (Bennett & Lanning, 2007). Contexts of mood and emotions have been

established as important to film and music recommender systems (Adomavicius et al., 2011) and are perceived as being more closely related to the user's experience than metadata related to the recommender dataset, e.g. genre (Tkalčič et al., 2010). However these have mostly focused upon areas of user 'emotional intelligence', i.e. self-understanding of own emotions (González et al., 2007), 'user allocation' of mood to an item i.e. a particular song (H.-S. Park et al., 2006) and 'mood information' tagged within an item's profile (Andjelkovic et al., 2016) or where emotions are expressed or extracted from content within blogs etc. (Fernández-Tobías et al., 2013). Modelling of Affective State within groups of people has also been attempted, however this has proved problematic, not only because a system will not be able to please all group members at the same time but also through the influence which individuals have upon other members' emotions (Masthoff & Gatt, 2006). User personality can determine user preference, therefore a 'preference model' is required to enable personalization of services and appropriate recommendations (Ono et al., 2007). User preferences may also change, not only according to the user's personality, but also the context such as mood, location, accompanying person, and so forth. Therefore, a user preference model is required to take into account both the user's personality and other situation specific contexts for various personalized services.

Perception is also a large field of research with a focus upon areas of user perceived effort, e.g. difficulty, the system's effectiveness and its outcome, e.g. satisfaction (Knijnenburg et al., 2012). Thus far the research into the area of actual perception of information provided within the recommendation, i.e. the descriptive text used to engage the user, has not been approached. Research into the area of perception has been limited to the perception of system performance, e.g. its usefulness (Pu et al., 2011) and a user's perception of transparency of the system when forming trust (Sinha & Swearingen, 2002). Though these measures have been shown to be good for assessing different aspects of recommender systems they do not address the 'cognitive effort' required to process the actual details of the recommendation.

While the methods of including physical and modal contexts within a recommender system provide input into making appropriate recommendations within recommender systems they thus far do not use

the context to determine cognitive behaviours. Without this understanding the knowledge of what is influencing levels of engagement that the user has with information displayed on a mobile device will be limited. The above is a key focus of this research and contributions to this effect are made in chapter five.

Having discussed the importance of context and its incorporation within e-commerce systems, including recommender systems, the following section now briefly discusses the use of in built smart-phone sensors to capture a wide range of contextual information.

2.8   Phone Sensors and Recognition of Contextual Phenomena

This section discusses the use of smart-device sensors and the insight these are starting to provide into the value of user contexts and the potentially heavy processing requirements that sensor use and data processing can produce. While smart-phone processing power and battery capability have advanced over recent years the use of resource hungry data processing algorithms can be problematic. Therefore mobile applications must still be resource efficient and power aware to ensure a suitable level of unobtrusiveness.

The momentum with which smart-phone technology has advanced in providing access to low cost sensors and social communication applications has stimulated a myriad of possibilities for the measurement and modelling of user environment and behaviour. Alongside the relatively mature mobile phone applications such as the microphone, camera and clock we now commonly have high connectivity, e.g. mobile data, Wi-Fi and Bluetooth, accelerometers, location awareness e.g. GPS and WiFi, and even touch-sensitive screens which all potentially provide behavioural indicators through regular daily use and their association with everyday activities. The introduction of other sensors aimed at the measurement of the atmosphere, e.g. humidity and temperature, have potential to provide a high level of insight into user environment and activities.

Smart-phones have been used to accurately determine user contexts. Primarily relying upon the accelerometer, applications have been used to gauge mood (Ma et al., 2012), stress (Giakoumis et al.,

2012) and exercise (Consolvo et al., 2008). Sensors can also be used to measure local environment: the microphone has been used to measure ambient noise to determine music levels, speech etc. to determine issues such as stress (Lu et al., 2012); phototransistors have been used to capture the level of light to gauge position of the mobile device i.e. pocket, bag, desk (Ma et al., 2012). Barometers, temperature and humidity sensors are also becoming available on some smart-phones and could be used to replicate experiments, including (Consolvo et al., 2008), (Lester, Choudhury, & Borriello, 2006), using bespoke devices that support useful activity detection. The differences in smart-phone placement, e.g. the difference in humidity between being in the pocket vs. in a bag, will increase the complexity in the categorisation of the sensor data when compared to bespoke, fixed devices.

Research that utilises smart-phone sensors has drawn upon behavioural patterns of phone use and the content of communication. Phone applications that include calls, email, SMS, web browsers and social networks, can be used to inform mood models (Likamwa et al., 2011), (Ma et al., 2012). Researchers have also drawn upon the connectivity of the phone (3G, WiFi) to utilise web accessible data focusing on location via GPS to help build a picture of the user's local environment and behaviours. A prime example would be weather information; downloading regular temperature, wind, atmospheric pressure and precipitation specific to a user's location has several uses including inferring mood and behaviour. There has been much interest in connecting weather with mood to determine behaviour, with interesting examples including effects on stock market trading (Kaustia & Rantapuska, 2013), (Bollen, Mao, & Zeng, 2011).

The smart-phone microphone is a valuable tool and one of the areas of focus within this research. Being robust to positioning it can be used to classify specific situational environment noises (Lu et al., 2009), (Delgado-Contreras et al., 2014). With human voice having comparatively unique features when compared to the sounds created by background activities, for example, typing, vacuuming, brushing teeth, crowd and street noise, they can therefore be simply extracted and used to model behaviour (Lu et al., 2010). Natural non-linguistic vocalisations e.g. a laugh or crying, can show displays of stress, boredom and excitement, all of which can be categorised reasonably effectively (Calvo & D'Mello, 2010). Though measurement of user speech has had particular success in

categorising sadness, anger and fear, it unfortunately has a lower accuracy to that of facial expression recognition (Calvo & D'Mello, 2010), and can be subject to severe distortion (Constantine & Hajj, 2012).

GPS and accelerometers have been used to infer user contexts i.e. position and activities and have been utilised in many research and commercial applications (Koldijk et al., 2012). GPS however has limited value in determining user activity. Though it can provide locational information and can be used to determine some activities such as 'travelling by car' it provides little depth when assessing indoor places and its use will consume excessive energy especially in continuous sensing situations (Kim et al., 2010). The smart-phone accelerometer however requires lower power and is computationally inexpensive when compared to GPS and other sensors such as the microphone (Lu et al., 2010). The accelerometer has a potential for identifying user gait (Nishiguchi et al., 2012), activities such as jogging, ascending - descending stairs, walking, sleeping (Kwapisz et al., 2011), and patterns of movement e.g. micromotion (Ma et al., 2012), all of which can provide insight into user behaviour.

On-line social networks including Twitter, Facebook and MySpace can be, when coupled with other tools or built in applications, used to support the understanding of personality traits (Stecher & Counts, 2008), user behaviour (Likamwa et al., 2011), (Bollen et al., 2011) and user moods (Likamwa, 2012), (Ma et al., 2012). Using data from typical smart-phone applications, including SMS, email and phone calls, a system can utilise statistical usage models and learn to estimate mood (Likamwa et al., 2011). Findings show that, depending on their mood, people tend to communicate with different people, and this seems particularly apparent when people are happy (Likamwa et al., 2011). Knowledge of activities can be realised through on-line social networks (Emiliano Miluzzo et al., 2008); people also create profiles to match their desired self-presentation (Stecher & Counts, 2008) therefore providing very rich information on themselves that can be used to inform context-aware recommender systems. MoodMiner, (Ma et al., 2012), uses communication data, e.g. call logs and texts, to support extraction of behaviour pattern and assessment of daily mood, however it is noted that mood has a strong time correlation and therefore changes little day-to-day.

Regular real-time data capture and post-processing can become a real issue for smart-devices (Lane et al., 2010). Unlike other sensors such as the accelerometer, using microphones to capture data requires a high sampling rate and can over-burden the available computational resources. Therefore a sensible sampling rate (duty-cycle) is needed (Emiliano Miluzzo et al., 2008). Voice activity detection can be used to reduce these overheads through calculation of background noise thresholds using specific features such as zero-crossing or signal-to-noise to identify usable speech input. Reductions can be further applied through encapsulated feature extraction and trigger reuse (Wagner et al., 2009). As a solution some systems rely on remote servers to complete the computational workload while the device continues with relatively little demand on resources. However, this method comes with the issue of data transmission between phone and server and in particular produces an impact on continuous sensing and real-time results (Lu et al., 2010). A more appropriate solution is to carefully manage requirements and aim to limit processing using lightweight classification algorithms (Lu et al., 2009).

While research has had success in using smart-phone data to develop personalised models, the results are thus far limited due to the nature and variety of human behaviours. Systems that require continued updates of contextual information can produce a considerable draw upon resources and make the device unresponsive. However, with balanced need-frequency management and careful choice of post-processing methods it is possible to reduce the impact of research system background processes.

2.9   Chapter Summary

With mobile smart devices becoming increasingly embedded within the on-line purchasing cycle e-commerce tools such as recommender systems need to adapt to ensure effectiveness and continued viability to businesses. This chapter has presented a detailed discussion investigating how a user's affective state and other contextual information can determine how a consumer perceives information and to what extent becomes involved in the purchase-decision process.

In this chapter the complexity of affective phenomena has been explored and a method suitable for computer based implementation has been identified in the form of Mehrabian's (1996) three

dimensional theory of emotion. The use of this tool will enable a quick reporting method for establishing user feelings alongside capturing situational contexts and experimental data.

With contextual variability being inherent to mobile devices the consumer is more likely to encounter situations that are detrimental to successful engagement with a product placement presented via a mobile device. This notion is critical to the advancement of m-commerce, however, while the importance of contextual information within the field of recommender systems is recognised it is still underdeveloped in terms of understanding the relationship between affective state, physical contexts and consumer behaviour.

In order to aid the development of a context-aware framework that considers the relationship between user affect-cognition, consumer behaviour and the physical environment the concepts of *unfavourable physical situations* and *disruptive contexts* are introduced. Here I postulate that these conditions have an effect upon user cognitive capacity and therefore their level of engagement.

This chapter has also investigated the concepts of Purchase-Decision Involvement and User Perception to provide insight into consumer engagement. I have discussed various information presentation styles used within the area of product marketing. Informed by this study it was postulated that particular methods will be more preferable than another depending upon the user's situation, in particular when considering the relationship between intensive disruptive contexts and the user's affective state. I have also postulated that user purchase-decision involvement will also be affected by disruptive contexts providing further insight into the levels of user engagement achievable using mobile devices.

The hypotheses developed above will provide a solid foundation on which to develop a novel prototype system that supports the *how* and *when* to present online advertising to the consumer. The following chapter discusses the methodology utilised in completing this objective.

3. Research Methodology

3.1 Introduction

While research efforts are beginning to establish an understanding of user affective, social and physical states and their relevance within context-aware systems (Adomavicius & Tuzhilin, 2015) it is only now with the advance of smart-phone sensor technology that research can truly leverage this knowledge within the area of mobile recommender systems (Lane et al., 2010).

Though research into context-aware recommender systems is now showing positive results through multi-criteria evaluation of both user generated content and environmental context, the utilisation of contextual information is still, thus far, limited. The focus of this research is to demonstrate that user contexts can be used to improve our understanding of how an individual reacts to information presented via a mobile device within different situations. I posit that understanding user behaviour within different contexts is critical to fully realise the potential for recommender system results through message customisation, especially within the developing area of m-commerce environments. To support this a number of experiments were conducted and developed a novel framework for recommender system personalisation. The final implementation of the framework demonstrates that utilizing user contexts to inform the likelihood of engagement can be used to improve the effectiveness of product placement within m-commerce.

Section 3.2 begins with an explanation of the research methodology used within this study. A rationale for the selection of the non-experiential approach and the study tools used is discussed. Section 3.3 introduces the approach to the sampling of data i.e. the targeted population, sample sizes and issues that arise using the non-probability, purposive sampling approach. In section 3.4 the issues of reliability and validity of data are discussed and the steps taken to mitigate these issues. I also argue that this approach in using *maximum variation sampling* enables the ability to identify patterns across a wider variation of sample which benefited the approach of conducting surveys in natural situational contexts. Ethical considerations are discussed in section 3.5 as is the approach taken to the different methods of deploying the survey questionnaires used in the experimentations conducted. Section 3.6

discusses the techniques used for all the data collection conducted and section 3.7 presents the instrumentation used to collect each of the different sets of data required to conduct this research.

3.2   Research Approach and Design

A non-experimental quantitative approach was applied within this study. Quantitative research utilises numeric, empirical data and is considered to provide objective and structured observations (Punch, 2013). While *experimental* research aims to provide strong evidence for cause-and-effect relationships through manipulation of variables, *non-experimental* research examines variables as they exist, i.e. no manipulation (Belli, 2008). The rationales for adopting non-experimental research are for reasons of ethical considerations, e.g. assigning individuals to an inappropriate group, and when variables cannot be manipulated as they are naturally occurring e.g. personality characteristics (Belli, 2008). The advantages of using non-experimental research are that they have the ability to be used within a realistic setting, large amounts of varied data can be collected with relative ease, and of course, multivariate statistics are available to analyse the data (Tayie, 2005). Due to the nature of this research the non-experimental convention is followed and while findings cannot be used as proof of causality, there are statistical methods available, including correlation analysis, to indicate potential relationships. While not providing definite cause it can, through careful consideration and presentation of logical arguments, suggest a *likely* conclusion for a causal relationship (Simon, 1954).

This research utilises methods of Survey research, namely the *self-administered questionnaire*, to collect the sample data. Questionnaires are ideal for conditions where the intended population is too large and a representative sample is needed. While this method of generalization can potentially come at a cost, measures of validity and reliability provide positive epistemology and support statements made via quantitative methods (Simon, 1954). The style of survey adopted in this research is an analytical survey which is used to ascertain why situations exist through examination of variables to test hypotheses developed (Tayie, 2005). Self-administered questionnaires are administered using three separate techniques. Depending on the maturity of the experimentation, either paper-based or

electronic methods are utilised. Electronic methods comprised of on-line surveys and bespoke Android applications.

3.3 Study Population and Sampling

To address the sampling requirements for the tests included within this research a minimum target number of participants is initially selected based upon Pearson's Correlation Coefficient and p-value (1) probability values as presented by (Bissonnette, 2015). Though strong correlations are sought for it is obvious not to expect perfect values and to hold with the general opinion that minimum correlations of 0.3 are acceptable. The online calculator (Soper, 2018) to produce the Pearson's Correlation Coefficient p-value results is used throughout.

$$\rho X, Y = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

Where,

$$cov = covariance$$

$$\sigma_X = standard\ deviation\ of\ X$$

$$\sigma_Y = standard\ deviation\ of\ Y$$

For all hypotheses herein a test for two-tail probability is used for calculating significance. For two-tailed probability testing, 50 participants are needed to achieve a probability confidence level of 99% for a 0.36 Pearson's correlation. This definition of 50 participants is initially followed in setting population sizes, however as the hypotheses develop larger population sizes are introduced. See the individual experimental results in chapter four for the exact figures of the number of participants and population-sample representation.

In the final experiment a sets of samples based upon whether using context-awareness or not is produced. To test the null hypothesis that the sample population means are the same, the Two Independent Sample T-Test (2) is employed using online calculator (Miller, 2013) to produce results:

$$t = \frac{\overline{X} - \overline{Y}}{s_p \cdot \sqrt{\frac{1}{n_x} + \frac{1}{n_y}}} \qquad df = n_x + n_y - 2 \qquad\qquad (2)$$

Where,

$\overline{X}$ = sample mean

$\overline{Y}$ = sample mean

s_p^2 = pooled sample variance

s_p = pooled sample standard deviation

s_x^2 = unbiased sample variance for X

s_y^2 = unbiased sample variance for Y

n_x = sample size of X

n_y = sample size of Y

For all experiments herein, survey participation was obtained via invites sent to University of Bedfordshire (Luton, UK) staff and students. Invites were managed via email and the University's virtual learning platform. In addition to this, friends and family were contacted via Facebook with a request to participate. While relatively unspecific, the subjects included in all sample sets were self-selected to meet the following criteria:

- be mentally sound in order to consent to participation

- be willing to participate

- be 18 years or older

- be of either sex or any race

The sampling method followed is non-probability, *purposive sampling* which suffers the issue of *bias* and lack of *sampling frame* (i.e. is not probabilistic, random sampling). This undermines any statement that attempts to extrapolate to a specific population (Farrokhi & Mahmoudi-Hamidabad, 2012). However, purposive sampling can be suitable for exploratory research design and there are a number of benefits to its use. In addition to the informal, low 'cost' considerations, the use of purposive sampling provides suitable access to a broad range of groups (Etikan, 2016). As the focus is

not on any specific user group this method is suitable for the needs of this research and is defensible as long as an experiment design audit-trail is provided to "precisely report circumstances in which the research was conducted" (Farrokhi & Mahmoudi-Hamidabad, 2012).

3.4 Reliability and Validity

While it is acknowledged that no experiment can be perfectly controlled and that non-qualitative experiments can have limited accuracy (Kirk & Miller, 1968), controls of *reliability* and *validity* are utilised to ensure research results are 'correct' enough to base conclusions upon. The use of reliability refers to the repeatability of experiments where user results will return the same if repeated (Belli, 2008). Both *reliability across time* (i.e. the same test is conducted at another time) and *reliability across samples* (i.e. results return the same for different demographics e.g. age groups) are considered. In this work, to negate issues of reliability across samples, all the experiments herein are conducted within a broad span of age groups, 18 to 45 plus. Issues of reliability across time is also somewhat negated through the unspecified times or locations required for user participation. While there may be specific situations where results are not entirely repeatable, this research focuses on in-the-wild experimentation with a broad approach to user and their situation produces wide-ranging sets of data. To help maintain these reliability factors the sample sizes used within the experimentations conducted were increased.

The premise of reliability also refers to the tools used within an experiment, for example if a user was to complete a test on two occasions and their results were similar it is possible to state that the tool is reliable. Where possible the tools used within this research are well known and proven to be reliable, otherwise Cronbach alpha (Cronbach, 1951) is used, this is a lower bound estimate of the reliability for psychometric tests for assessing tools and is used here to report findings in individual experiment results analysis.

Validity relates to ensuring quality of measures taken within an experiment i.e. actually measuring what was intended and not actually for another use (Belli, 2008). It is therefore essential to ensure that evidence is provided to be able to demonstrate validity of a particular route vs. an alternative analysis

(Jacelon & O'Dell, 2005). Validity is generally separated into several types, and while the measures taken reinforce all the aspects of validity within the experiments, this research is primarily concerned with *internal validity* and *external validity*. Internal validity can refer to the possible effects to results achieved due to manipulation of an independent variable (e.g. controlling the level of noise in the laboratory). Internal validity is also subject to the issues of the *confounding variable* (Belli, 2008) i.e. inadvertently measuring something else other than the variables being studied to produce the expected outcome. As the experiments were primarily designed to be in-the-wild and non-experimental this phenomena produces a threat to the analysis of the results because there are many potential uncontrolled situational aspects that could form the result expected.

Careful experimental design reduces this potential reduction in internal validity. With the aim to demonstrate the effect of negative contexts on user behaviour existing tools are used to measure both the user's affective state and cognitive constructs of involvement and perception. These phenomena have previously been shown to have correlative relationships (Myers & Sar, 2015), (Hansen, 2005). This relationship and how it is affected within negative contexts is explored by separating the data into levels of contextual readings e.g. a high level of distractions vs. a low level of distractions and then assess the correlation between the two phenomena. Separating the data provides two fundamentally different situational groups that will demonstrate an effect of the context on user behaviour if it exists. Where it is found that the user behaviour is affected within one and not the other group it is plausible that other variables are producing the effect seen, however it is also probable that these will be directly related to the situational context i.e. other negative contexts. This is corroborated within the results as shown in chapter five which demonstrate that multiple contexts are seen to affect user behaviour.

In another aspect of validating data and actually measuring what is intended, the concept of *external validity* is concerned with the extent that generalisation can be applied to the results i.e. over time or to other people. As previously mentioned the approach used here is to use in-the-wild experiments to achieve a natural setting for the experiments, which has been shown to improve the level of external validity (Bracht & Glass, 1968). So, while not being able to follow the use of randomised data due to

the use of non-probabilistic sampling, the methods used in the implementation of the experiments herein help ensure validity of the data.

This research primarily relies upon naturalistic settings for its experiments to ensure their external validity, however by also increasing the size of the sample sets has helped reduce the effects of extreme scores and extraneous factors (Farrokhi & Mahmoudi-Hamidabad, 2012). Furthermore, the sampling method used within this research, purposive sampling, involves the researcher determining what information is needed and who can provide it for the study to be a success (Etikan, 2016). The process involves the identification and selection of individual groups who are able to provide the information needed. While the use of portable smart-devices is prevalent within society it was essential to ensure that user participation within the experiments was conducted using a smart-phone. Selecting this specific user group ensured that participation involved users of small devices who were also exposed to collaborative on-line resources, e.g. Facebook, and product placement via different methods utilised within m-commerce. This was achieved using methods of distribution including email, Facebook and the University's on-line learning portal.

It is generally accepted that the range of an attribute, for example 'level of education', used within comparable experiments should be narrow as this similarity supports the achievement of reliability and validity (Farrokhi & Mahmoudi-Hamidabad, 2012). However the use of *maximum variation sampling* provides the benefit of supporting the ability to identify patterns across the variation (Etikan, 2016). This method is followed because the surveys were to be conducted in natural settings and therefore open to wide variances in situational contexts. While this potentially affected reliability and validity of results of individual experiments, the basic design of the experiments were repeated throughout and therefore produced a layering of results that, through the overlapping of findings, provided a relatively consistent outline for developing a framework.

3.5   Ethical Considerations

Research, as well as being conducted with due diligence, requires honesty and integrity to respect a participant's human rights. The studies undertaken within this research did not involve any divergence

from a participant's daily routine, whether physical or psychological. In other words participants were not subject to any risk whilst undertaking any activities involved in the studies.

Care was taken to ensure that participants fully understood the nature of the study in which they participated, that it was voluntary and that they could withdraw at any point. Where a paper-based questionnaire was used the participants were informed via a consent form prior to completing the questionnaire (see Appendix A). For the experiments that utilised on-line surveys (Google Forms) the participants were notified via detailed electronic communication, e.g. email, (see Appendix B). The Google Form used in each questionnaire, in addition to the recruitment message, also confirmed that the participation was completely anonymous (see Appendix C and Appendix D). Where an Android application was used to distribute a questionnaire, the method of instructing the participant of the project and the participation considerations was managed in several complementary steps. The participant was contacted initially using a method of electronic communication (see Appendix B), further information was presented via Google Play, an on-line application distribution platform. See Appendix E and Appendix F for the screenshot representation of the distribution page and a separate webpage containing a privacy policy as required for Android applications that record sensitive data; to view just the text used within these webpages see Appendix G. Finally the participant's consent was managed within the application by providing a route to allow the withdrawal from the study at any point (see Appendix H). This was enforced with the participant being able to uninstall the application from their phone at any time.

The confidentiality of recovered data was maintained at all times. Competed paper-based consent forms were kept in a secure cabinet after the questionnaires were anonymised using ascending code numbers. The data recovered from the studies using Google Forms was completely anonymised by the application and stored electronically. The Android application utilised a secure server for receiving user data. The data was anonymised before being encrypted using AES (Advanced Encryption Standard) and then RSA (Ron Rivest, Adi Shamir and Leonard Adleman) encryption methods before being uploaded to the server. Once recovered all data was stored electronically and maintained within the cloud using Dropbox, a secure file hosting service.

Permission to conduct the studies involved in this research was submitted to and granted by the University of Bedfordshire's Ethics committee (see Appendix I and see Appendix J).

3.6   Data Collection Techniques

This research involved several experiments that utilise proven tools within questionnaire format. These included predefined User Involvement tools, e.g. Product Involvement (Laurent & Kapferer, 1985) and Purchase Decision Involvement (Mittal, 1989), User Perception utilising the semantic differentials method (Bruner, 2009) and Three Dimensional Emotion Theory in the form of the Pleasure-Arousal-Dominance emotional state model (Mehrabian, 1996). Key to this work is the use of a bespoke questionnaire that collected user data based upon subjective impression of user environment and activity, see section 3.7.4 for details. Together these tools are combined into a single self-administered questionnaire. Self-administered questionnaires (SAQ) are questionnaires that are designed specifically so there is no intervention between the researcher and the participant during data collection. This method allowed us to pursue a number of different experiments using SAQs ranging from paper based through to smart-phone application based, without changing the style of the questionnaire or the participant-research relationship.

All questionnaires described below utilise scaled, closed-ended, questions. Tayie, (2005), suggest that questionnaires should aim to be closed-ended; however, though obtaining information similar to conducting interviews, results will have less depth. Concerns of this nature are offset by the benefits that closed-ended questions provide. Not only do closed-ended questions lend themselves to statistical methods, they are easier to administer and analyse by the researcher but are also efficient for the respondent (Wilson, Jones, Miller, & Pentecost, 2009). This is primarily due to closed-ended questions requiring less time than open-ended questions and thus reducing the risk of questionnaire abandonment (Crawford & Lamias, 2001).

The initial experiment was a paper-based SAQ (see Appendix A), focusing upon user involvement. This questionnaire was administered in one location (a classroom) over two sessions. The consent forms, with attached questionnaire, were distributed to students who had agreed to participate. Once

completed and returned by the students the two parts were separated after giving both a unique reference number. This method supported a high level of anonymity when analysing the data but also allowed the participant to withdraw their data if they so required.

Also conducted were two separate experiments that utilise an on-line survey application (Google Forms) to build questionnaires. University staff and students were contacted using University email and the University's virtual learning platform. In addition to this, friends and family were also contacted via Facebook with a request to participate. All prospective participants were sent an invite with a call to action, including a description of the project, a note on privacy and a link to the survey. Google Forms provide a method of quick and simple questionnaire development and also some simple analysis, however the main benefit is that the collection of the data is completely anonymous and can be downloaded in Excel format for analysis purposes. The two questionnaires developed using Google Forms are listed in Appendix C and D.

A number of versions of a purpose built Android application were developed by the author, each version being used for an individual experiment. Over time this application developed from an early stage application distributed questionnaire to a context-aware model for predicting user involvement and perception. The application, SiDISense (Situational Decision Involvement Sensing System), was used in a total of four experiments all utilising a very similar process of implementation. Note that all are discussed as individual experiments in section 3.8, however the general implementation is as follows. Potential participants were contacted in the same manner as the Google Forms experiments. University email and virtual learning platform were used to send invites to participate to University staff and students. Facebook was also used to contact friends and family in a similar manner as described above. However instead of a link to an on-line questionnaire, a link was provided to the Google Play store. Google's Play store provides a simple and low cost management system for distributing applications and is widely used within the sector. It provides compulsory sections within an application's distribution page for describing the application purpose and associated information, including a privacy policy (see Appendix G). Once installed on the participant's smart-phone the

application will request the user to acknowledge the information presented within the consent section of the application (see Appendix H) before fully activating the program and collecting data.

Once a response to the questionnaire has been completed by the participant, the application encrypts the results and uploads the encrypted data to a secure server where it is decrypted for analysis. Note that data is anonymised through the use of a random generated user identification number, however using this number the participant is still able to withdraw their data from the experiment if they so wish. While the application is still installed on the device the 'call to action' requesting the user to complete the questionnaire will repeat at regular intervals. Once the user feels they have submitted enough times, by uninstalling the application their participation ends.

In chapter four further details are presented for each individual experiment with a focus on purpose, implementation and development to the next stage. Prior to this the following section provides details of the instrumentation used within the questionnaires and their purpose within the research conducted.

3.7   Instrumentation

The research conducted by the author utilised a total of five instruments in the form of survey questionnaires. These included instruments developed as part of previously conducted research and new items built specifically for the purpose of this research. Not all instruments were used within each experiment. Chapter four describes their implementation within each experiment, where applicable.

The previously existing instruments that were used in this research included Mehrabian's (Mehrabian, 1996) multidimensional model for *measurement of user affect*, Mittal's *measure of user product involvement* (Mittal & Lee, 1988) and similarly another to measure *user purchase-decision involvement* (Mittal, 1995). This research also utilises a widely used concept of *semantic differentials* (Bruner, 2009) to determine a measurement of user perception.

The final notable instrument used in this research was developed by the author specifically for the purpose to understand the effect of environment and physical behaviour upon a person's decision involvement and perception of information presented via mobile devices. The novel *disruptive*

contexts questionnaire was developed based upon findings explored within the literature review (chapter two). Also beneficial in forming this concept were informal peer discussion based upon aspects of familiarity of people and places, and the effects of disruptions within the workplace. This led to the development of a short seven question survey as described further in section 3.7.4. The following subsections describe the instrumentation used in detail.

3.7.1   A Multi-Dimensional Measure of Emotion

While there are many techniques available that have been shown to be effective in the measurement of user affect, mood and emotions however this research uses a well-established three dimensional model that is straightforward for the researcher to implement and which is also relatively unobtrusive for the participant to complete. For all the experiments user affective state is captured using Mehrabian's (Mehrabian, 1996) Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness (PAD) dimensional model. The three dimensions in PAD are addressed separately so that the participant only thinks about one dimension at a time. The user can rate themselves along a particular dimension e.g. using a one to five Likert scale, however I also follow popular practice where the user is requested to self-report their affective state using a psychological tool called the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994). This three factor graphical scale provides a quickly understood, effective user interface and directly transfers to the three dimensional PAD dimensions. Note that each scale is measured from one up to five with five being the maximum value. See figure 4 for an example of the pleasure-displeasure scale in an on-line format.

Where the Self-Assessment Manikin (SAM) is used in paper format (see Appendix A) or via a Google Forms questionnaire (see Appendix C) each scale is presented to the user one after the other. The SAM tool provides a set of images which are used to represent the scales, and I also provide a brief description of the purpose of the scale. Together, this provides guidance to completing the scale and also a visual cue to the participant which improves recall and efficiency where the test is repeated multiple times.

Figure 4: Screenshot of section of a Google Form questionnaire representing the pleasure-displeasure dimension for capturing levels of negative-positive user affect state

Where this scale is utilised within the Android application (SiDISense), the implementation is identical except that the scale's description is temporally presented to the user in the form of a popup when the heading of the scale is tapped, see figure 5. This method supports the participant by providing the information guide for completing each scale but also reduces the size of the interface, thus increasing its efficiency as the participant becomes more familiar with its use. Keeping all three scales visible on the screen together with the submit button simplifies the interface, thus supporting quick completion of the task, perception of burden and the reduction of abandonment rates (Crawford & Lamias, 2001).

Apart from the slight variations of implementation between experiments, the use of the Self-Assessment Manikin is typical of use, an existing instrument providing an established implementation of the PAD dimensional model.
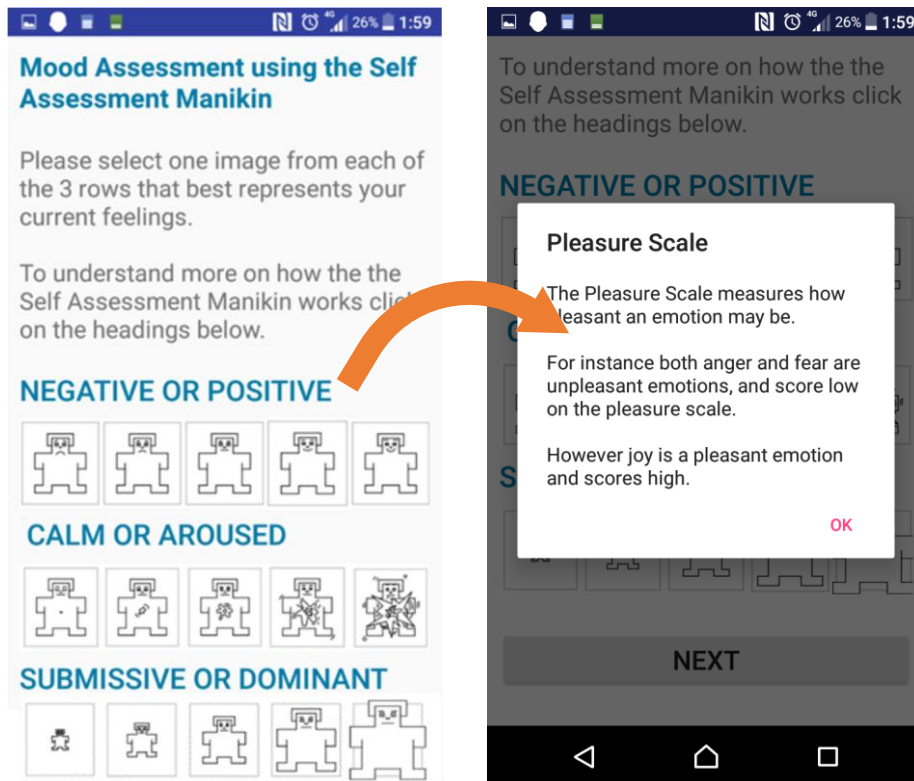
Figure 5: Screenshot of the Android implementation showing the three SAM scales and interactive headings

3.7.2   Measures of User Involvement

In the investigation into user-product involvement I identified two main areas of interest, tools for which are presented below. Product-level Involvement and Purchase-decision Involvement are existing measures and were selected for their robustness, simplicity and their applicability to e-commerce. These measures were selected with an intention to support the hypotheses that user involvement is affected by the relationship between user affective state and user contexts.

3.7.2.1   Product Involvement

In an attempt to understand how consumers engage with products, brands and the general advertisement process *product involvement* has been widely researched and a number of measurement tools have been developed, see discussion in section 2.5.1. To determine a participant's level of product involvement I utilise part of the Consumer Involvement Profile tool (Laurent & Kapferer, 1985). As per Mittal's experience I also utilise three specific questions that focus on the *perceived*

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importance of the product (Mittal & Lee, 1988). The participant rates each question using a Likert scale with maximum and minimum labels of strongly agree and strongly disagree. The three questions are demonstrated below using the product *computers* as an example:

1. *Computers* are very important to me

2. For me *computers* do not matter

3. *Computers* are an important part of my life

While not investigating the other facets of the participant's involvement profile i.e. risk, sign and hedonic, it provides a short, focused questionnaire which is quick and intuitive for the participant to complete, and a valuable insight into the user-product relationship. The results of the three questions convert to a single parameter using equation (3).

$$\sum_{i=1}^{n} \left(q1_i, \left(\text{scale}_{size+1} \right) - q2_i, q3_i \right) \qquad (3)$$

Where,

$q = value\ on\ likert\ scale$

$S_{size} = number\ of\ points\ in\ likert\ scale$

$n = number\ of\ instances$

$i = iteration$

Figure 6 demonstrates the three questions and their typical layout in the experiments where they were used within this research. Note that the underscore would be replaced by a type of product e.g. computers. As the design of the experimentation developed this tool is dropped from later iteration to reduce the perceived burden on participants.

Figure 6: Screenshot of the paper-based implementation for capturing
Product-Level Involvement

3.7.2.2   Purchase-Decision Involvement

Similar to the Product-level involvement scale the Purchase-Decision Involvement is an important part of understanding a user's potential engagement with products presented via e-commerce. Measurements of Purchase-Decision Involvement (PDI) are used in an attempt to capture a user's anticipation mind-set towards a purchase and is effective especially when measured as close to the event as possible (Mittal, 1989). To measure purchase-decision involvement on primarily high-involvement products I utilise Mittal's revised version of the PDI scale (Mittal, 1995), see discussion in section 2.5.1. The scale is very straightforward to replicate and comprises of three questions that determine the user's view of:

1. How much they care about a product

2. Whether it is important to make the correct choice

3. Whether they were concerned with the outcome of making that choice

The results from the three questions convert to a single parameter, using equation (4), and the final result represents the user's Purchase-Decision Involvement. This original tool developed by Mittal, (Mittal, 1989), is used throughout the experiments focusing on Purchase-Decision Involvement.

$$\sum_{i=1}^{n}(q1_i, q2_i, q3_i) \qquad\qquad (4)$$

Where,

$$q = value\ on\ likert\ scale$$

$$n = number\ of\ instances$$

$$i = iteration$$

No changes to the format of the tool are made except where method of presentation required a different approach, e.g. paper based, on-line or Android implementation. Figure 7 provides a screenshot of the Android implementation of this scale where instead of listing the choices the user touches the 'please select' link in the interface where a popup presents the participant with a choice presented in Likert format. Note that the questions presented in figure 7 are aimed, in this instance, at the participant's involvement with houses.
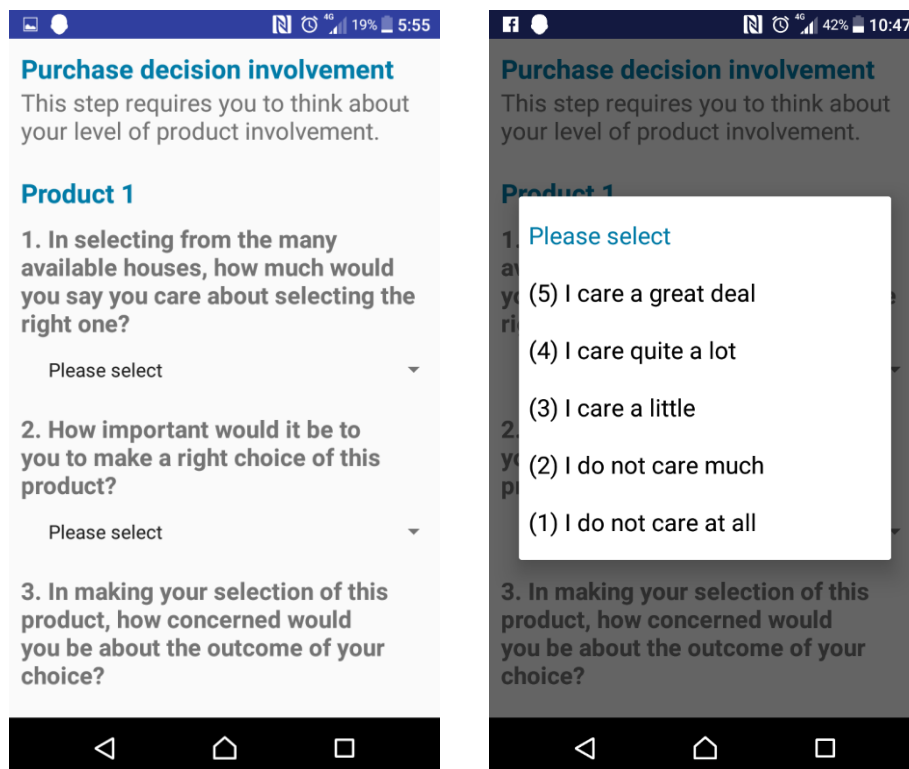

Figure 7: Representation of the design for capturing Purchase-Decision Involvement

3.7.3   A Measurement of User perception

While there are techniques to help increase the likelihood of a user browsing into a purchaser, it is still not entirely clear how situations influence the effectiveness of these techniques. Through the

measurement of a user's perception of a mobile advert the aim is to gauge the likelihood of user acceptance of the information provided. Multiple measurement scales have been developed in an attempt to measure our attitude towards adverts, and Bruner et al., (1995), suggests the use of semantic differentials is not limited to a single approach. Therefore a very short and broad measure for attitude towards an advert can be used to gauge a user's general perception accurately. Three very generic semantic differentials are selected to capture a measure of formed attitude and also encapsulate the majority of those shown to have been widely used previously, see section 2.5.2 for a deeper discussion.

The semantic differentials selected are:

1. Effective-ineffective

2. Appealing-unappealing

3. Believable-unbelievable

Throughout this research this measure using the above semantic differentials will be referred to as *eab-perception*. Though seemingly trivial these three semantic differentials can be used to provide a realistic insight into user message perception within real-life situations using mobile devices. In the experiments each advert statement is subject to the eab-perception questionnaire with each differential being rated using a five point psychometric Likert scale, e.g. for the differential *effective-ineffective* a range from 1) Very ineffective to 5) Very effective is used. This method enables us to produce a level of positive response to a statement. As per typical use of a multi-item measurement scale the equation (5) is used to produce a single value for use as an output.

$$\sum_{i=1}^{n}(e_i, a_i, b_i) \qquad\qquad\qquad (5)$$

Where,

$e = value\ on\ likert\ scale\ (effectiveness)$

$a = value\ on\ likert\ scale\ (appealing)$

$b = value\ on\ likert\ scale\ (believable)$

$$n = number\ of\ instances$$

$$i = iteration$$

To assess the suitability of this approach Cronbach alpha (Cronbach, 1951) is used, see equation (6). Cronbach alpha is a lower bound estimate of the reliability of psychometric tests and is widely used for multiple item measures.

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k}\ \sigma_{y_i}^2}{\sigma_x^2}\right) \qquad (6)$$

Where,

$$k = number\ of\ scale\ item$$

$$\sigma_{y_i}^2 = \ variance\ associated\ with\ item\ i$$

$$\sigma_x^2 = \ variance\ associated\ with\ the\ observed\ total\ score$$

An online calculator is used to implement the above equation (Wessa, 2017). The results for individual experiments were found to be satisfactory and are presented within the relevant experiment sections as described in chapter four.

3.7.4   Disruptive Contexts Questionnaire

As per the discussion, within section 2.6.2, it is expectd that contexts, such as noise in the environment and user activity, will play a major part in supporting the development in the understanding of how best to engage with the consumer. The contexts utilised in this research were not an exhaustive list of environment or behaviour contexts, however these met the research objective which focused upon disruptive contexts and their influence on user behaviour. The initial pool of questions focusing upon disruptive context are below:

- Familiarity of your immediate environment

- Level of noise in your immediate environment

- Your amount of activity within the last couple of minutes

- How comfortable do you feel in your current surroundings?

- Number of people in your immediate vicinity

- Familiarity with people in your immediate vicinity

- Current level of engagement / interaction with people in your immediate vicinity

The list above, which was developed for the experiment described in section 4.2.2, is refined later to become the novel *disruptive contexts questionnaire* as low impact questions were either removed or redesigned (see Appendix D for an on-line implementation). The questionnaire is discussed further below with each question categorised within Adomavicius et al.'s framework for context aware recommender systems (Adomavicius et al., 2011). The use of the disruptive contexts questionnaire is a novel concept within context aware systems.

In Adomavicius et al.'s work (Adomavicius et al., 2011) user context is sorted into four types that impact a mobile service environment, these are *physical*, *social*, *interaction media*, and *modal*. Below describes how the identified disruptive contexts are categorised within the physical and social contextual types. Also presented are the use of modal and interactive media contexts and how they are formed.

Physical: In this research it is hypothesised that the physical contexts captured can be used to determine the level that situation stressors reach will enable an understanding of the impact of negative situations upon decision involvement and information processing. The key situation stressors identified in chapter two (section 2.6.2) comprise of *level of noise*, *amount of distraction*, *amount of activity* (current or very recent) and *number of people in the immediate vicinity*. In this part of the questionnaire the users are requested to rate themselves for each using psychometric Likert scales. The minimum and maximum labels used with the Likert scales were as follows:

- Level of noise (Very quiet ~ Very noisy)

- Level of distraction (None at all ~ Lots of distractions)

- Amount of activity (Very low ~ Very high)

- Number of people (I am alone ~ it is very crowded)

Social: For the social category of context section 2.6.2 identifies that our perceptions of places and people are entwined (Paulos & Goodman, 2004), and that familiarity of these will influence performance (Goodman & Leyden, 1991), feeling and attitudes (Moreland & Zajonc, 1982), and trust (Luhmann, 2000). Here I ask the participant to rate their *familiarity of immediate environment* and *familiarity of the people therein*. Both use a Likert scale with labels as follows:

- Familiarity of environment (Very unfamiliar ~ Very familiar)

- Familiarity of people (Unknown to me ~ Well known to me)

Interaction media: Initially this research's approach is to simply request the user to identify which kind of device they are using i.e. PC, laptop, tablet or smart-phone. This allows us to investigate phenomena for both large and small devices to determine whether the use of different devices produced similar results. The reader should note that as I advanced my research, these findings influenced the focus of later experiments to solely upon smart-phones.

Modal: The category of modal contexts is the most complex as it includes a user's goals, motivations, mood, perceptions and cognitive capabilities (Adomavicius et al., 2011). The approach to this category is as follows. As previously stated I measure the participant's affective state using Mehrabian's (Mehrabian, 1996) Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness dimensional model. I also focus somewhat on the participant's cognitive capabilities through measurements of involvement and perception. Together these measures are key to proving the hypothesis that the introduction of disruptive context will affect the relationship between user affective state and other modal attributes including cognitive capacity and manner of perception.

Each question within the disruptive context questionnaire is currently used as a stand-alone item, i.e. not reduced to a single value. While this approach could be investigated further in the future it was found that while concatenation of effects from disruptive contexts can increase the correlation found in affective-cognitive relationships, the use of even singular disruptive contexts can also be enough to provide suitable results to form an insight. This led to iterative reductions in the length of the

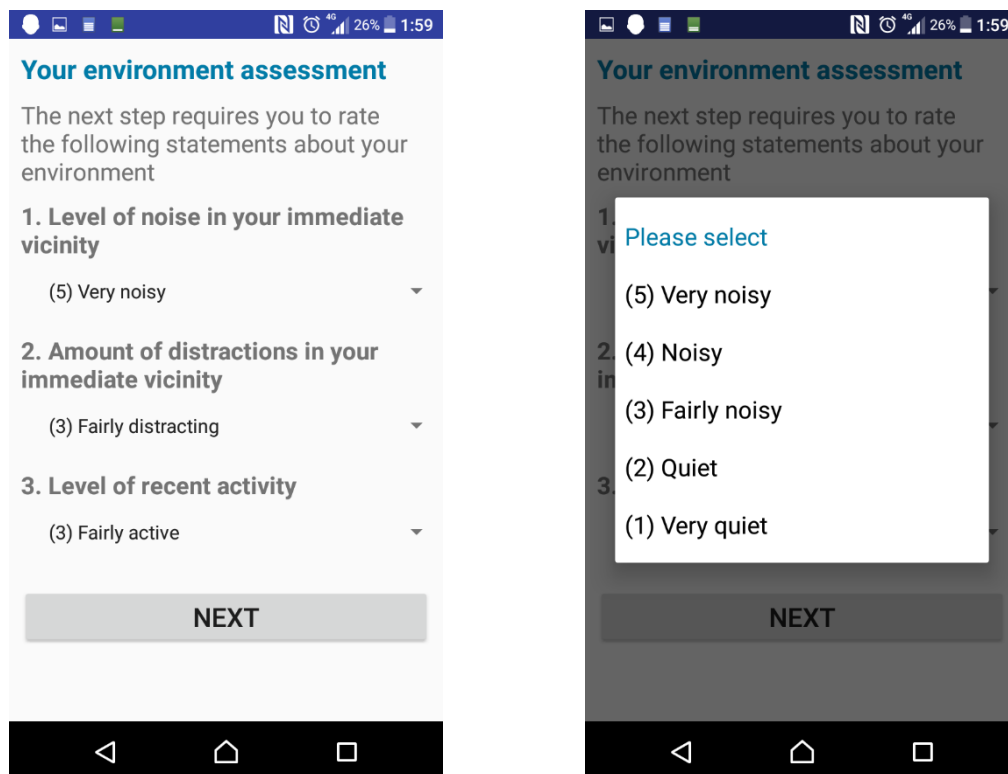questionnaire as research focus is applied to elements that pursue previously found significant findings.

Figure 8: Screenshot of part of the Android implementation showing the Likert scale capturing levels of user perception of environment and activity contexts

Once again the reduction of questionnaire size supports the decrease in burden upon the participant answering a questionnaire. However this should not distract from the importance of the complete disruptive context questionnaire and the additional exploration of the concept planned for a later date to fully incorporate it into applicable context-aware systems. Figure 8 presents a screenshot of the final android implementation for the contextual section of the questionnaire that had been reduced in length to three questions that focused solely on physical contexts.

3.8 Chapter Summary

This chapter has presented an overview of the research methodology adopted for this work. The research design, population sample, ethical considerations and data collection techniques are all

discussed to provide an insight into the author's considered approach to the research and thus the findings as presented in chapter five.

Section 3.2 discusses briefly the approaches of quantitative research to support the selection of non-experimental research using self-administered questionnaires as the desired method of data collection. It was identified that statistical methods of analysis, including correlation analysis, can provide insight into likely causal relationships where logical consideration is given to analysis of results. Also presented was the appropriate attention required to reliability and validity of data. Issues potentially associated with in-the-wild, non-experimental approach to experimentation were identified, investigated and moderated to ensure minimal impact on research findings.

I finally discuss the use of different instrumentation that together make up the survey questionnaires used in this research. Whilst different deployment methods were used to present these questionnaires, i.e. paper-based, on-line and Android applications, their implementation remained relatively consistent throughout. Measures of user emotion, involvement and perception were introduced alongside a novel approach to employing situational contexts in the form of the *disruptive context questionnaire*. The relevance and importance of these measures within the research undertaken were explained, as were the details of their use and, where applicable, their development over time.

The following chapter provides in detail the implementation of all the experiments conducted within this research. Each stage of research is discussed as a cycle which presents the objective of the research, together with the development and deployment of the questionnaire instrumentation used within each experiment. The final cycle presents the culmination of research efforts in the form of an implementation of a novel context-aware framework for use with mobile recommender systems.

4. Implementation of Research

4.1 Introduction

Several experiments were conducted in the form of questionnaire surveys. These included paper-based questionnaires, on-line surveys using Google Forms and a bespoke Android implementation named SiDISense (Situational Decision Involvement Sensing System). In addition to these experiments a method for using neural network pattern recognition tools was developed for classifying different environment and user contexts. These were initially built using the programming language Java for testing, and adapted to work on Android, a smartphone operating system, for the concluding experiment.

I was keen not to follow other researcher methodology of stimulating mood states through techniques such as the use of mood eliciting videos within a laboratory environment, e.g. (Myers & Sar, 2015), or indeed maintaining control over the environment whilst the experiments were conducted. Instead I favoured utilization of natural 'in the wild' contextual phenomena and the majority of the experiments were conducted remotely as the participant went about their everyday lives without intervention from the researcher.

As demonstrated in figure 9 there are two domains of research focus, 1) User Perception and 2) User Involvement. Each domain of research develops from either a paper-based questionnaire or a straightforward Android implementation to finally become a complex Android application (SiDISense) that utilises background services and Machine Learning to determine aspects of environment and user behaviour. In the final experiment research efforts are concatenated into a single implementation which uses neural network pattern recognition to classify levels of environmental distractions and user activity. This classification is then used to determine levels of user perception and user involvement before the system chooses whether to present (and how to present) an advert to the user.

Details of Tools Used

Initial Contexts
- Familiarity of immediate environment
- Level of noise
- Amount of activity in last few minutes
- Level of comfort in current surroundings
- Number of people in immediate vicinity
- Familiarity with people in immediate vicinity
- Level of engagement / interaction with people

Disruptive Contexts
1. Familiarity of immediate environment
2. Level of noise
3. Amount of distraction
4. Current level of activity
5. Number of people in immediate vicinity
6. Familiarity with people in immediate vicinity

Semantic differentials
- Effective / ineffective
- Appealing / unappealing
- Believable / unbelievable

PAD
- Pleasure / displeasure
- Arousal / nonarousal
- Dominance / submissiveness

Marketing Styles
1. Mental imagery
2. Detail processing
3. Low effort
4. High effort
5. Low risk
6. High risk
7. Fear appeal
8. Optimistic appeal

Activity measurement
- Recording and pre-processing accelerometer data
- Length of recording 15 Minutes
- Windowing of data (number of windows 15)
- Using MAX(xyz) for each point
- Using Mean and Standard Deviation of each window

Disruptions measurement
- Recording and pre-processing microphone data
- Length of recording 60 seconds
- Windowing of data (number of windows 60)
- Using Mean and Standard Deviation of each window

Pattern recognition / classification
- Matlab recognition and classification application
- Weka - Open Source Machine Learning Library
- Neural Network Classifier

Cycle One

Mobile Application

USER PERCEPTION

An Investigation into Perception of Textual Presentation Styles

- Marketing Styles (1,2,3,4,5,6,7,8)
- PAD
- Semantic differentials
- 38 statements

Paper-based

USER INVOLVEMENT

Initial Study of User Involvement

- Product-Level Involvement
- Purchase-Decision Involvement
- PAD
- Initial Contexts (within single controlled situation)
- Two products

Cycle Two

Google Form

USER PERCEPTION

Exploring the Effects of Situational Contexts on User Perception of Advertisement Styles

- Product-Level Involvement
- Marketing Styles (1,2,7)
- PAD
- Semantic differentials
- Disruptive Contexts (1, ..2, 3, 4.. 5, 6)
- Five products

Google Form

USER INVOLVEMENT

Exploring the Effects of Situational Contexts on Purchase-Decision Involvement

- Purchase-Decision Involvement
- PAD
- Disruptive Contexts (1, ..2, 3, 4.. 5, 6)
- One product

Cycle Three

Mobile Application

USER PERCEPTION

Categorizing User Perceptions of Advertisement Styles within Disruptive Contexts

- Marketing Styles (1, 2)
- PAD
- Semantic differentials
- Disruptive Contexts (2, 3, 4, 5)
- Twenty five products
- Activity measurement
- Disruptions measurement

Mobile Application

USER INVOLVEMENT

Categorizing Levels of User Purchase-Decision Involvement within Disruptive Contexts

- Purchase-Decision Involvement
- PAD
- Disruptive Contexts (2, 3, 4, 5)
- Twenty five products
- Activity measurement
- Disruptions measurement

Matlab / Java application

TRAINING OF ALGORITHMS

Development of Classification Routines

- Pattern recognition / classification

Cycle Four

Mobile Application

USER PERCEPTION
USER INVOLVEMENT

Predicting Levels of User Purchase-decision Involvement and Perception of Advertisements

- Purchase-Decision Involvement
- Marketing Styles (1, 2)
- PAD
- Semantic differentials
- Disruptive Contexts (3, 4)
- Twenty five products
- Activity measurement
- Disruptions measurement
- Pattern recognition / classification

KEY

Method

AREA OF FOCUS

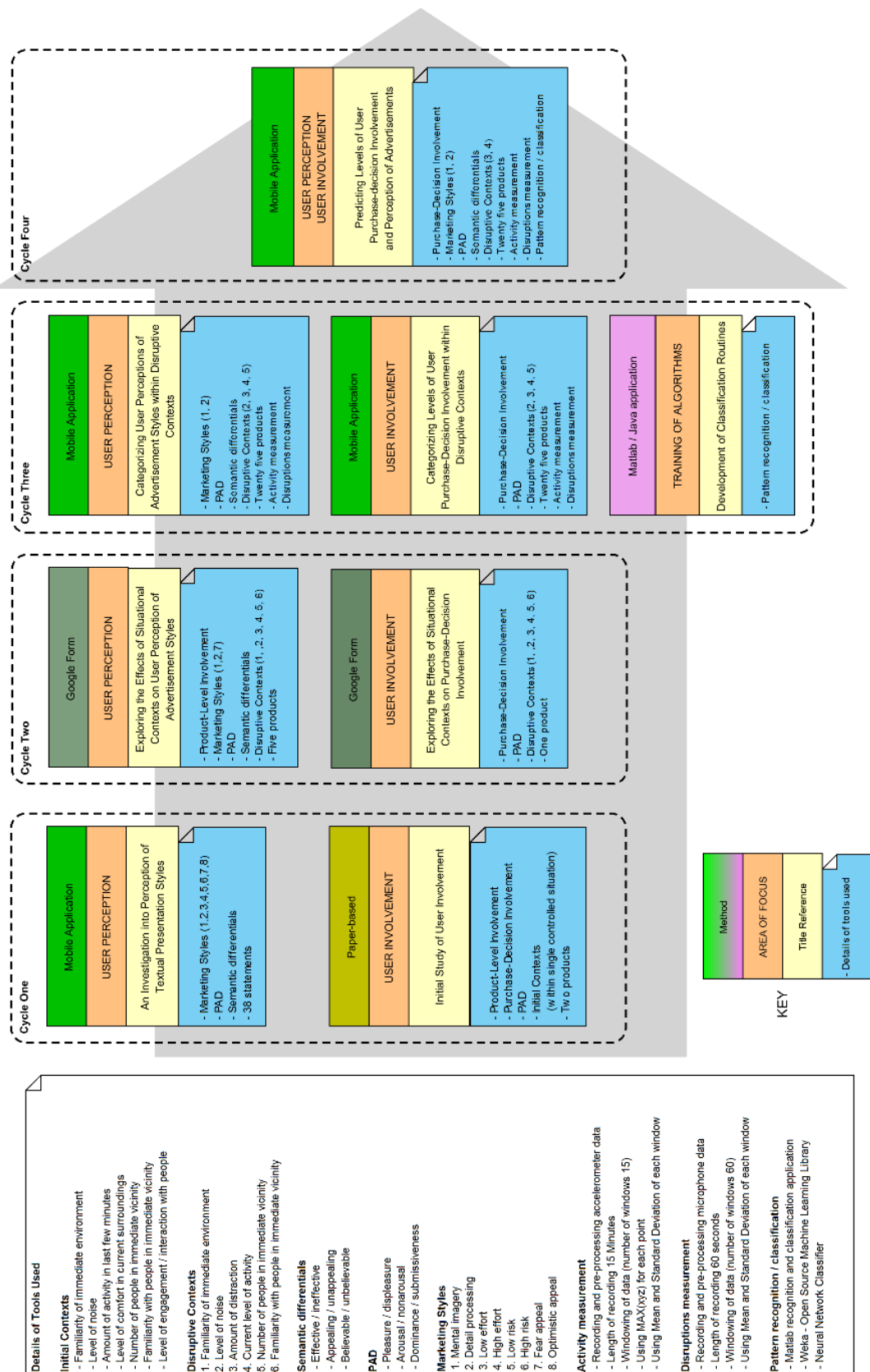Title Reference

- Details of tools used

Figure 9: Research cycles and experimentation overview

The research totalled seven surveys completed over four cycles. Each cycle is a revision and refinement of research approach. Details of each stage in experimentation are presented below in the following subsections. This research was carried out over four cycles of experimentation, each refining and building upon the previous output. Throughout this chapter, figure 9 can be referred to, to provide visual cues as to the use of the instrumentation and how each supported the development of subsequent experiments which are discussed in the following sections.

4.2   Cycle One

Cycle one focuses on introducing the two research themes: User Perception and User Involvement. The experiments include a paper-based survey and an initial Android application both of which provide insights into *user – context* relationships that lead further to the development of the novel concept of *Disruptive Contexts*.

4.2.1   An Investigation into Perception of Textual Presentation Styles

In this initial experiment I investigated how a user's affective state affects their perception of textual statements presented via a mobile device. I hypothesized that someone will have a different perception of mobile information depending upon their mood, specifically along the pleasure-displeasure dimension of the PAD tool described in chapter three. I also hypothesise that different presentation styles used to display information will determine specific levels of perception depending on the user's affective state.

Styles were initially categorised for information presentation as follows, *mental imagery, detail processing, low effort, high effort, low risk, high risk, fear appeal* and *optimistic appeal*. The use of these categories was developed based upon findings uncovered within the literature review and are summarised thus:

- Mental imagery vs. detail processing – A user's positive mood increases the ability to undertake mental imagery processing and that the capacity to evaluate detailed information is increased during periods of negative mood (Myers & Sar, 2015).

- Low effort vs. high effort – Positive moods lean towards a shallower, heuristic processing due to a lowered cognitive capacity whereas sad moods suffer more effortful processing potentially due to a more problematic environment (Martin, 2003).

- Low risk vs. high risk – It is expected that a user will be more risk adverse and will endeavour to maintain a positive sensation, whereas when in a negative state they will be more likely to engage with riskier purchases (Brave & Nass, 2002).

- Fear appeal vs. optimistic appeal – When in a positive mood a user would be persuaded more by a positively framed message than would a person in a negative mood and vice versa, i.e. those in a negative mood would be more susceptible to fear appeals (Wegener et al., 1994).

For testing the above hypotheses thirty-eight statements split between the categories were produced (see Appendix K for the complete list). Each statement type is image free and minimal in formatting with the focus being on a basic message presented to the user for interpretation. The structure for each type of statement used is described as follows, complete with an example:

- Mental imagery – statement that only induces mental imagery i.e. no analytical processing e.g. *"Run your hands on the soft satin fabric, it's going to be a peaceful sleep tonight"*

- Detail processing – statement that provides information that needs to be analysed or compared, e.g. *"Guaranteed for 5 years our satin bed sheets hold their colour and shape for 10 times longer than our closest competitor"*

- Low effort – easy to read statement with shorter word length (18 word average), e.g. *"A revolution in sizing, fit and thinking. Slimming side seams & subtle boot cut flatter your shape"*

- High effort – complex statements with longer word length (34 word average), e.g. *"In contrast, a traditional survey of the same subjects produced only 54% agreement between subjects (where both subjects acknowledged having the conversation) and only 29% agreement in the number of conversations"*

- Low risk – statement that presents no risk and is very general, e.g. *"The patented SuperLite has 60% higher resolution than its nearest competitor# providing 20% higher resolution together with crisp text and images"*

- High risk – statement that presents a situation with an element of risk, e.g. *"Having a good understanding of the stock market can be very rewarding financially however underperformance is common and large amount of stocks fall, losing value long term"*

- Fear appeal – statement that infers that inaction will lead to a negative result, e.g. *"Don't lose out! One day left on this offer"*

- Optimistic appeal – statement that infers that an action will lead to a positive result, e.g. *"Click here for future offers to get the best deal for your summer break"*

The longest statement was 343 characters long (including spaces) with the average being 136 characters long. The reader should note that some of the statements are structured in a way that they fit several categories. For example a small number of high risk and high effort statements fitted the definition of a detail processing statement. The reverse however is not always the case.
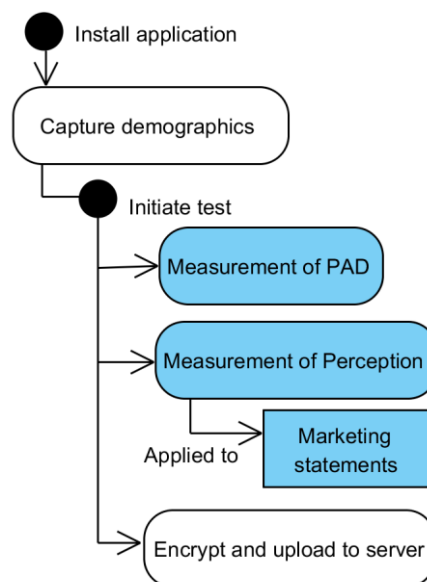
Figure 10: User Perception – procedural structure of Android application

For this experiment an Android application was developed. The procedural design, i.e. the details of the tools used within the experiment, is shown in figure 10. The user was polled during a period when they were using their smartphone but making a call. If the user chose to participate at that point then a measurement of PAD was taken and then four randomly selected statements were presented for the user to asses. Each statement was presented in turn and the participant was required to rate the statement using the *eab-perception* tool produced for the purpose of capturing the user's perception, see section 3.7.3. For this experiment, using the eab-perception scale produced a Cronbach's Alpha (Cronbach, 1951) internal consistency measure of Cronbach $\alpha = 0.79$ which is considered acceptable.

4.2.2   Initial Study of User Involvement

Experiment two introduced the second domain of research undertaken, User Involvement. Rather than focusing upon the user's interaction with information, e.g. perception of product advert details, the introduction of Involvement explored how a potential purchaser is currently committed to a product type and their engagement in the purchasing process of this product. This experiment also introduces a contextual questionnaire which later, after revision, became the novel Disruptive Contexts Questionnaire. From experiment one I concluded that additional situational contexts were potentially affecting the relationship between affective state and cognitive phenomena. The contexts explored included a broad range of contexts which focused on aspects of interaction between the user, environment and other people in that environment. Following this second experiment the concept was refined with a focus upon truly disruptive contexts.

This experiment was conducted using a paper-based survey; figure 11 presents the structure of the questionnaire and the instrumentation used within, see appendix A for the template questionnaire. The survey was completed, within a University seminar room, over two different sessions to collect participant feedback on high-involvement product i.e. computer laptops. Note that the instrumentation used to measure involvement with product types was implemented with no product information or images, therefore participant feedback was provided based entirely on existing opinion and subjectivity.
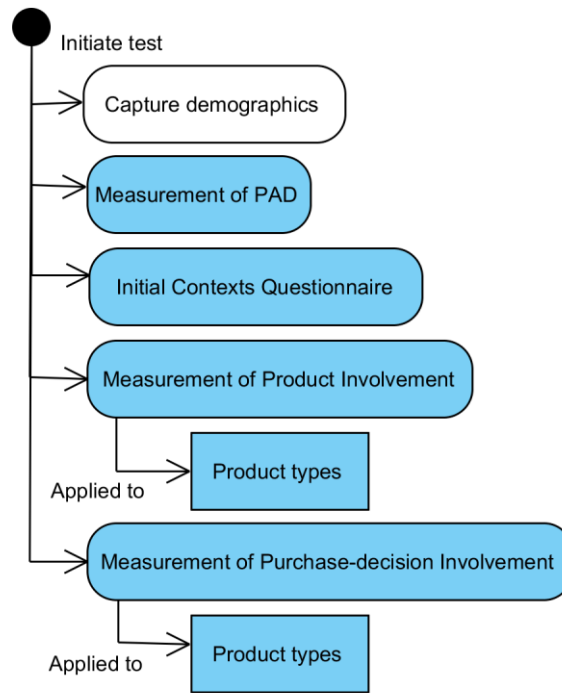
Figure 11: Product and Purchase-decision – procedural structure of paper-based survey

4.3 Cycle Two

The second cycle focused upon a refinement of the experiments completed in cycle one. Both themes of research were followed, i.e. user perception and user involvement, this time utilising on-line surveys developed using Google Forms. Two experiments were undertaken to explore further initial findings with a focus on demonstrating the hypothesis that disruptive contexts affect user behaviour whilst using mobile devices.

4.3.1 Exploring the Effects of Situational Contexts on User Perception of Advertisement Styles

The purpose of this experiment was to explore further the concept of information perception as it is presented within different environments. This experiment revisited and developed the concept of user perception and user affective state relationships which determine the effectiveness of advertising styles, as previously investigated in the experiment described in section 4.2.1. In addition to this I also

explored the effect of situational contexts upon this phenomena using the revised context questionnaire which had been distilled to form the *Disruptive Context Questionnaire*.

The survey used within this experiment was developed within Google Forms; the structure and instrumentation used was as presented in figure 12. The survey started by capturing basic info, i.e. *gender, age, device type* and *location*. The SAM representation of PAD is then used to capture user affect and then the physical and social contexts were captured via the disruptive contexts questionnaire. The last stage, which assessed the user's perception, required the participant to assess a mock-up of a basic e-commerce advert which included style specific text and a generic yet product related image. Three presentation styles were explored, *mental imagery*, *detail orientated processing* and *fear appeal*. Note that both the advert text and the image follow the presentation style (see Appendix C for implementation of the Google Form and the advert mock-ups used for each style). The adverts were specifically unbranded to ensure the participant's impartial subjectivity. This experiment ran for a single high-involvement product: smart-phones.
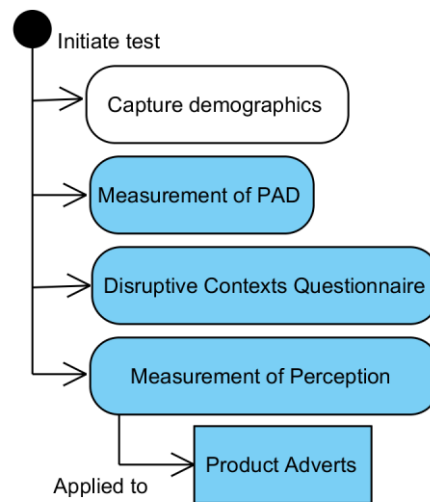
Figure 12: User Perception – procedural structure of on-line survey

As per experiment in section 4.2.1 the participant was required to rate the advert using the *eab-perception* tool as produced for the purpose of capturing the user's perception, see section 3.7.3 for a full description of this method. The experiment's results produced a Cronbach's Alpha (Cronbach,

1951) internal consistency measure of Cronbach $\alpha = 0.82$, which is considered acceptable for needs of this research.

4.3.2   Exploring the Effects of Situational Contexts on Purchase-Decision Involvement

As per the experiment described in section 4.3.1 this survey also utilised a Google form as an on-line questionnaire. It explored further the relationship between user affective state and purchase-decision involvement together with the revised disruptive context questionnaire to examine in more depth the effect of environmental and behavioural contexts upon this phenomena.

The survey ran using a total of five high-involvement products/services *smart-phone, holiday, laptop computer, insurance plan* and *refrigerator* (see Appendix D for the implementation). Figure 13 present the structure of the questionnaire and the instrumentation used. As before the survey started by capturing basic data e.g. *gender, age, device* and *location*, PAD was then used to measure user affect and then the disruptive contexts questionnaire was used to measure the physical and social contexts. This was followed by a final section, the purchase-decision involvement questionnaire. This section repeated the questionnaire for each of the five high-involvement products, each iteration provided no product information or images so feedback was provided based entirely on existing opinion and subjectivity.
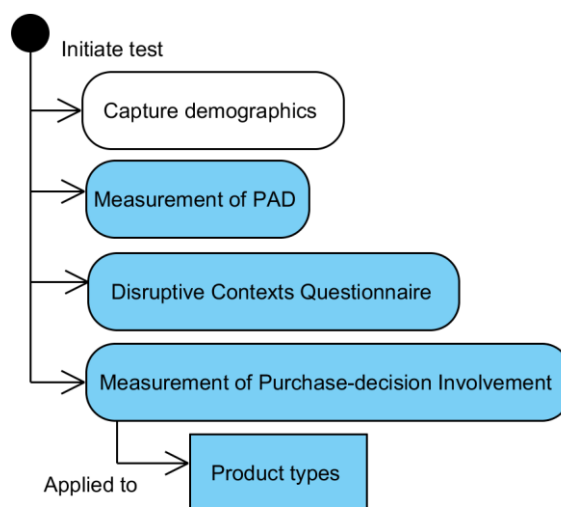
Figure 13: Purchase-decision Involvement – procedural structure of on-line survey

4.4 Cycle Three

The experiments completed within cycle three involved similar processes as described in experiments within cycle two. However in cycle three I used a bespoke Android implementation of the instrumentation. In these experiments the Android application utilised background services to manage when the survey was initiated. The background services started the survey at regular intervals – in this case every fifteen minutes. The participant could then choose whether to open the survey or ignore it, the service that manages this process then reset itself after sixty seconds if the survey was not started.

The timings used in the application were selected based upon previous experimental findings from cycle two. Where the participant had reported recent activity this was categorised as *approximately fifteen minutes*, therefore when attempting to determine the level of a participant's activity I extract features from a timeframe of fifteen minutes of accelerometer data. For determining levels of disruption the time frame was categorised as *current* therefore when capturing packets of sound for categorising levels of noise and levels of disruptions. Over a timeframe of sixty seconds sound was recorded and then features extracted whilst the participant was completing the survey.

The use of personal data, and in particular sound recordings, required ethical consideration to maintain participant privacy. In experiments described in sections 4.4.1 and 4.4.2 the application extracted features from the data recorded and then uploaded the extracted feature set to the server. The initial recordings of data on the phone were then deleted. Section 4.4.3 describes this process together with the methods used in the identification of features and the development of routines used to classify data.

As I wanted the test subjects to complete the experiment multiple times, these experiments required simple to use, efficient interfaces to ensure a user's continued engagement. An uncomplicated interface designs was used as was reducing page sizes by providing information using popups, these were used less as the participant became familiar with the application. Also, when the Android application was first initialised, the basic user data (age and gender) was captured, therefore it was not

asked for again. These steps were introduced to reduce the load upon the participant and hopefully encourage them to participate more than once.

A total of twenty-four 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, hi-fi stereos, champagnes, washing machines, fashionable clothes, health care packages, cosmetics, sofa suites, fridge freezers, home broadband packages* and *video streaming packages*. Note that Music CDs and Film DVDs, were also used in the experiment described in 4.4.2 but were dropped for the experiment in 4.4.1 as providing a generic advert description did not suit these products.

The final process in the sequence of events for both experiments required that the results for each instance of the completed questionnaire be encrypted and uploaded to a secure server. The encryption process utilised was as follows. For each survey created file an AES encryption key is produced, the survey created files are then encrypted using their corresponding AES key. Finally each AES key is encrypted using RSA encryption. The RSA encrypted keys and the AES encrypted files are uploaded to the server, thereafter these are decrypted on a local desktop PC for later use.

4.4.1 Categorizing User Perceptions of Advertisement Styles within Disruptive Contexts

This experiment developed further the hypothesis that disruptive contexts influence the relationship between a user's affective state and their perception of advertisement styles. For this experiment the focus narrowed to provide emphasis upon the advertisement styles of mental imagery and detail orientated processing. Utilising the Android platform with a larger range of products ensures that the focus was on mobile devices, in this case smartphones. It also provided the ability to engage with the participant multiple times and enabled real-time data to be captured as the device was used day-to-day. Access to real-time data supports the development of a dynamic system as would be required in a commercial application. The procedural design of the Android application and the implementation of instrumentation is shown in figure 14 and follows the description within the above section.
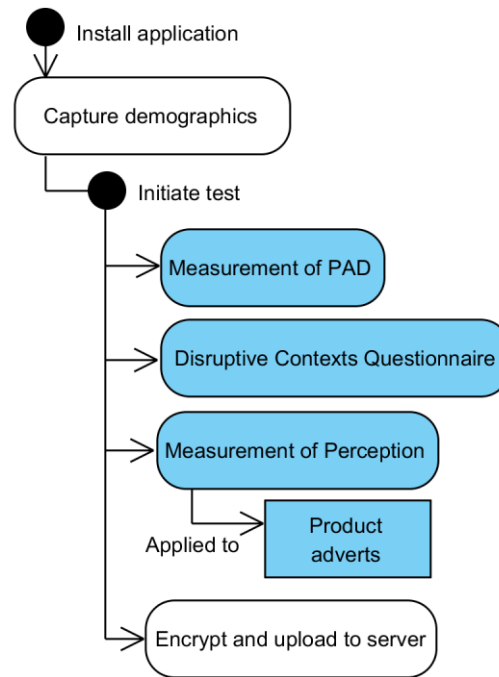
Figure 14: User Perception – procedural structure of Android application

As per previous experiments the survey started by capturing the participant's affective state using the Self-Assessment Manikin tool developed by (Bradley & Lang, 1994). The user was then presented with context statements related to their behaviour and physical environment using the disruptive contexts questionnaire which had been reduced to four questions, *level of noise, amount of distraction, amount of activity (current or very recent)* and *the number of people in the immediate vicinity*.

In the final section the participant is asked to select four products from the complete list of product names displayed in a grid format. These were then presented in basic adverts using either mental imagery or detail orientated processing writing styles using html templates that the application linked to. The four products selected were randomised and then shown in alternative order i.e. first mental imagery, next detail processing, and then repeat. The detail processing advert comprised of a bullet point list of four to six factual statements whereas the mental imagery advert compromised of two to three short paragraphs written to induce the mental imagery process i.e. requesting the reader to 'imagine'. Both the mental imagery and detail processing styled adverts for a particular product use the same unbranded image (see Appendix L for an example of a product formatted for both writing

styles using HTML/CSS). The text for each was also limited to very generic, unbranded, product based information (see Appendix M for text and images used for each product used in the experiment).

Once again the participant reviewed all four adverts presented using the measurement of perception tool, *eab-perception*. As mentioned previously this method enables us to capture a level of positive response to an advert. As before, to assess the experiment results Cronbach's alpha (Cronbach, 1951) consistency measure is used and this experiment achieves a desirably high result of Cronbach α = 0.85.

4.4.2 Categorizing Levels of User Purchase-Decision Involvement within Disruptive Contexts

This experiment utilised the same Android application as per the experiment described in section 4.4.1. All aspects are implemented identically to the previous Android implementation except for the final section of the survey. Once the participant's affective state and their perception of disruptive contexts were captured the user was then presented with the list of products which they assessed using the purchase-decision involvement tool, see figure 15 for procedure structure of the application.

The twenty six product names are simply listed in a grid for the user to select, see figure 16a. The user could not select this item again until all products had been reviewed, this ensured that the review of the products was reasonably distributed. Note that only a couple of users returned more than twenty-six questionnaires, the additional results above the twenty-six were not included to ensure that iterations of seeing the same product advert did not affect participant perceptions. As per previous purchase-decision involvement experiments the products are shown with no product information or images so feedback was based upon existing subjectivity of the product type, see figure 16b for the implementation of rating products using the PDI assessment tool.
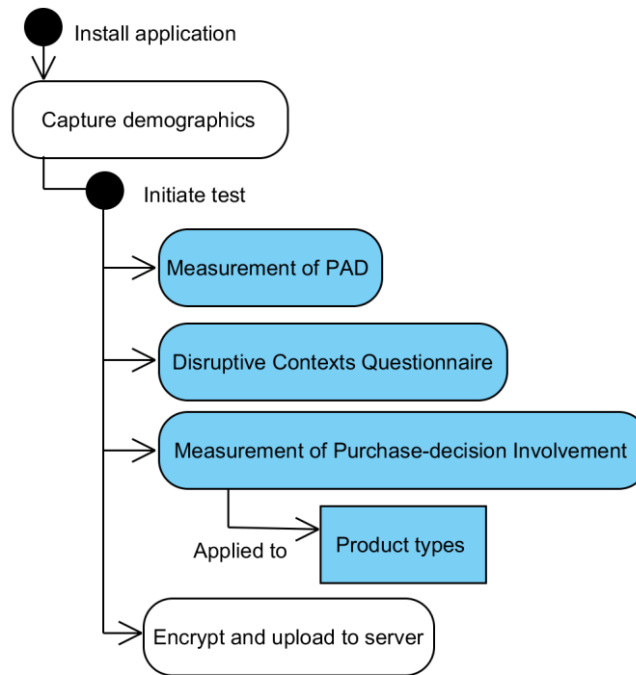
Figure 15: Purchase-decision Involvement – procedural structure of Android application
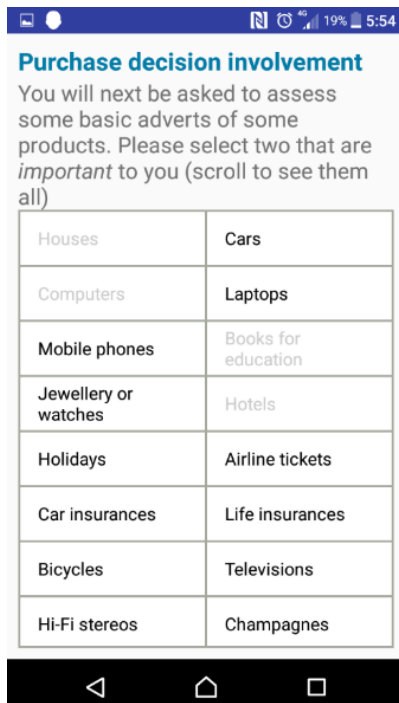
Figure 16a: SiDISense user interface
- selection of products
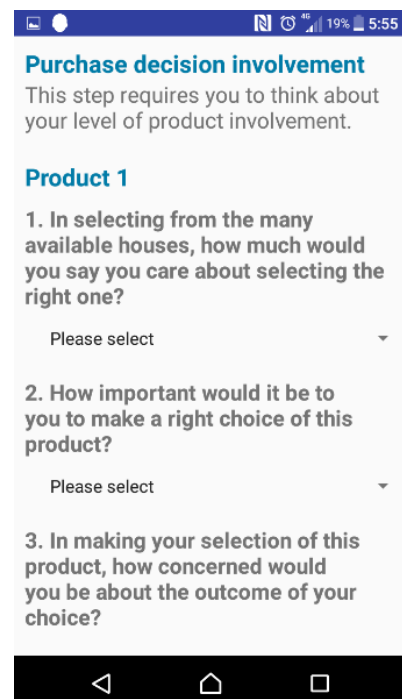
Figure 16b: SiDISense user interface
- rating of products using the PDI

4.4.3   Rapid Development of Classification Routines

4.4.3.1 Introduction

The final cycle of experimentation requires the Android system to be able to analyse user affective state and disruptive contexts to facilitate prediction of user levels of perception and decision involvement of product related information. This research focused on automatic classification of disruptive context whilst using the PAD dimensional self-reporting tool for a baseline measurement of user affective state. Together these are used with conditional logic to determine the likelihood of user response to product information presented via a mobile device.

Before developing the classification routines, a study of examples implementing feature identification and classification was undertaken. A method was selected to collect a number of feature samples from each instance in a dataset to support efficient classification of specific physical contexts. This method is applied to both the accelerometer data and sound recordings.

Initial experiments are completed using routines developed in Java using off-the-shelf libraries to enable the supervised training of feature data for pattern recognition requirements. From the labelled training data this method produces an inferred function which can be applied within an Android application. Once successfully trained the algorithm and inferred function are then used within the Android application to classify different contexts, primarily user activity and environment distractions. These steps are discussed in more detail in the subsections below.

4.4.3.2 Identification of feature sets

Machine learning encompasses a wide ranging set of tools for making predictions from data and there is a plethora of research examples that have attempted to classify data collected from mobile devices. Whether identifying behaviour of users online using social networks (Kosinski, Bachrach, Kohli, Stillwell, & Graepel, 2013) or classifying environmental audio signals (Delgado-Contreras et al., 2014) machine learning algorithms support entities in making data-driven predictions or decisions. To ensure that pattern classification techniques are effective it is imperative that the identification of

usable features is completed with care. Feature extraction is a process that reduces data whilst preserving the information of a signal (Agostini, Longari, & Pollastri, 2003).

The aim was to identify suitable solutions for feature identification for classification of aspects of audio and accelerometer data but which also minimised its effect upon device performance. While both types of data contain complex features that can be extracted and which have in the past been shown effective in use for classification of specific events, it was determined that the use of statistical features for identifying relatively basic features would suffice.

Examples where statistical features have been used to identify complex activities such as walking, running and jumping from accelerometer data (Figo, Diniz, Ferreira, & Cardoso, 2010) demonstrate that these features should be useful in supporting accurate identification of simple levels of activity between high and low. Standard statistical features have also been shown to be effective in characterising audio signals (Delgado-Contreras et al., 2014).

To effectively apply statistical features to a dataset, the data requires windowing, i.e. rather than ascertaining a feature for the whole of the dataset, the features (number of features) required will be extracted for multiple subsets (number of windows) within the data. This will provide an array of features with a length that equals *number of features* x *number of windows.* There are many windowing algorithms which overlap segments of data (windows) by a specific amount in order to suppress discontinuity and the resulting spurious high frequencies – examples include, amongst others, Hanning, Hamming and Blackman windowing functions. However, while useful these can impact performance and should be used with caution and implemented in an efficient lightweight manner where used with mobile devices (Emiliano Miluzzo et al., 2010). Therefore a simple, non-overlapping, windowing approach of statistical features was used, for example mean and standard deviation. This approach was followed for both accelerometer data and microphone recording data.

I initially recorded and labeled a small number of samples of each data type (accelerometer and audio). A Java application was developed to extract features and utilise prebuilt machine learning libraries to classify the data; see section 4.4.3.3 for more detail of the application and tools used

therein. In the first instance the following features were extracted, *mean, variance, standard deviation, maximum* and *median*. Feature arrays were created using a number of window sizes to ascertain a suitable length that would allow the accurate classification of data. The result of this process led to a window size of *one second* for the microphone recording and a window size of *one minute* for the accelerometer data being acceptable for needs of the research. The feature set was also reduced to only include the *mean* and *standard deviation* for each window, as the use of additional features provided minimal increase in accuracy which did not warrant the increase in device overhead produced by the classification routine.

4.4.3.3 Development and implementation of classification routines

As the experiments collected data that was labelled by the participant using a Likert scale I chose to utilise a supervised training method for pattern recognition. The method of back propagation was used to train a neural network using the data mining software Weka (Frank, Hall, & Witten, 2016). In addition to a standalone application, the developers of Weka provide a set of libraries that can be implemented within Java. Together with details of the General Public License, the program files are available here: https://www.cs.waikato.ac.nz/ml/weka/. Within the experimentations I developed Java software applications using a stripped down version of the Weka libraries available here: https://github.com/shamtastic/Weka-Stripped. This application was used to process both data types i.e. accelerometer data and microphone recording to construct a classification routine that was then applied within Android after some modification (see Appendix N for example Java classes). The Weka training algorithms use a specific file structure that holds details of each feature captured and their actual value (see Appendix O for a sample), therefore the feature extraction routine is applied before being saved to the Weka format.

To initially demonstrate that statistical features and the neural network methodology would be sufficient a small dataset was collected by the researcher within controlled environments to test and develop the routines required. Both accelerometer and microphone data were captured and converted using an extraction routine which extracted the required statistical features for a set of window

lengths. This provided different levels of information onto which the training-classification routines could be applied. As part of this process I had to balance accuracy against load on the Android device, therefore a setup that produced a good classification output whilst using the smallest number of windows as possible. As mentioned previously the one minute of recorded microphone data is processed using sixty windows with mean and standard deviation values being calculated for each, see windowing function shown in equation (7).

$$w(x) = \frac{\sum X}{n}, \sqrt{\frac{(X-\overline{X})^2}{n-1}} \qquad (7)$$

Where,

$n = sample\ size$

$\overline{X} = mean$

$x = number\ of\ windows$

Similarly the fifteen minutes of activity data utilises fifteen windows with mean and standard deviation values being calculated for each. However the maximum of each xyz axis point needs to be captured and this new array has the windowing function applied to it, see equation (8).

$$max\{x, y, z\}_i^n = \frac{1}{3}(x_i + y_i + z_i + |x_i - y_i - z_i|) \qquad (8)$$

Where,

$x = x\ axis\ value$

$y = y\ axis\ value$

$z = z\ axis\ value$

$n = number\ of\ instances$

$i = iteration$

Once suitable feature sets were determined for the training algorithm the extraction routines were then modified for use within the Android application used in the experiments conducted in cycle three (see Appendix P for Android classes implementing Weka libraries). Together the two experiments

generated a total of 303 audio feature files and 140 accelerometer feature files. The discrepancy between the two figures was caused by an error in implementation within one of the experiments which was not discovered until late in the data gathering. While unfortunate there was enough data from the two experiments to produce suitable classification of the two datasets. Once the data collection was complete the neural network training Java-Weka implementation was applied to produce the classifier for use within the final Android experiment in cycle four. The following section presents the results achieved from the training and testing of the labelled data and the final implementation of the classifier function.

4.4.3.4 Classification routine results

The data feature files captured are all paired with the subjective feedback supplied by the test participant using the Likert scale. Each filename is partly populated with a numeric number that represents the response for each question asked, i.e. with the question 'How noisy is it?', the response to very noisy would be 'five'. This not only provides easy facilitation of the file classification during training but also allows ad hoc rule sets to be used. While all disruptive context questions were scaled from one to five, the decision logic developed via the results as presented in chapter five did not require that level of granularity. I therefore ran the classification against three levels of rule sets to produce different classification models. As expected the reduction in the number of classes increased the success rate in the testing of the classifier. The first set uses the five classes of {1, 2, 3, 4, 5} as per the direct results from the user Likert responses. The second rule set reduced the model to three classes {1, 2, 3} i.e. low, medium and high values by shifting the second class to the first class and the fourth class to the fifth class. Similarly the third rule set is reduced once again to just two classes {1, 2} i.e. low and high values. See the logic used for reducing the number of classes in the table of results below.

The Weka libraries provide a number of methods for assessing the results of the classifier. The *evaluateModel()* method takes all the testing files, in this case 25% of the full data set was used and then returns a number of results ranging from the Kappa statistic and the root mean squared error. For

presentation purposes I use the number *Correctly Classified Instances* and the *Coverage of cases (0.95 level)* as indicators of the level of success in the classification process. Figures shown in the tables below demonstrate five cycles of the training and testing routines to establish an overall success rate. The Weka libraries also support k-fold Cross Validation via the *crossValidateModel()* method. This method uses the full dataset and a standard of ten k-folds to produce the cross validation output. The Cross Validation Accuracy is calculated using the equation in (9).

$$CVA = \frac{truePositives + trueNegatives}{truePositives + trueNegatives + falsePositives + falseNegatives} \qquad (9)$$

Again, five iterations of the training and the cross validation routines was completed for each data set. Results are shown in the following tables, table 1 (level of noise), table 2 (level of distractions), table 3 (number of people) and table 4 (amount of recent activity). The results show that the classifying model applied to the audio feature sets performed consistently well for all the associated environmental contexts i.e. *level of noise, level of distractions* and *number of people.* However as previously mentioned the reduction of classification classes not only suited the final experiments needs but also, as expected, increased the rate of successful classification. Therefore the final classifier for *level of distractions* which is used in the final experiment used the low, medium and high classes for classification.

As with the classification of the audio feature-sets, the accelerometer feature sets were also classified using three rule sets to classify the context of *amount of recent activity*, table 4. The use of the five classes failed to provide a suitable classification accuracy however the three class classification performed better producing a 71.4% classification of test instances. The logic developed as presented in chapter five for use in the final experiment required only a classification of either low or high levels of activity. The classification using these two classes achieved an average accuracy of 78.1% in correctly classified instances and was deemed suitable.

Table 1: Results from testing of classifier for *level of noise*

Rule Set	Correctly Classified Instances	Coverage of cases (0.95 level)	Cross Validation Accuracy
class = user_selected	64.4444 % 68.8889 % 66.6667 % 60 % 77.7778 %	77.7778 % 73.3333 % 77.7778 % 68.8889 % 82.2222 %	0.719472 0.742574 0.737074 0.736799 0.736799
If user_selected > 3 THEN class = 3 If user_selected = 3 THEN class = 2 If user_selected < 3 THEN class = 1	82.2222 % 73.3333 % 77.7778 % 93.3333 % 75.5556 %	86.6667 % 80 % 91.1111 % 93.3333 % 80 %	0.825083 0.782178 0.851485 0.839934 0.841584
If user_selected > 3 THEN class = 2 ELSE class = 1	95.5556 % 95.5556 % 95.5556 % 91.1111 % 93.3333 %	100 % 100 % 95.5556 % 93.3333 % 95.5556 %	0.930693 0.927393 0.919692 0.917492 0.914851

Table 2: Results from testing of classifier for *level of distractions*

Rule Set	Correctly Classified Instances	Coverage of cases (0.95 level)	Cross Validation Accuracy
class = user_selected	64.4444 % 80 % 71.1111 % 71.1111 % 75.5556 %	77.7778 % 86.6667 % 71.1111 % 75.5556 % 80 %	0.749175 0.735974 0.726073 0.718647 0.718152
If user_selected > 3 THEN class = 3 If user_selected = 3 THEN class = 2 If user_selected < 3 THEN class = 1	86.6667 % 93.3333 % 75.5556 % 80 % 88.8889 %	91.1111 % 93.3333 % 80 % 86.6667 % 88.8889 %	0.79868 0.806931 0.80418 0.805281 0.807261
If user_selected > 3 THEN class = 2 ELSE class = 1	91.1111 % 88.8889 % 95.5556 % 88.8889 % 91.1111 %	97.7778 % 93.3333 % 97.7778 % 91.1111 % 95.5556 %	0.953795 0.960396 0.961496 0.953795 0.953795

This reasoning is followed because it became apparent through the results achieved from the research that splitting a set of data into two was sufficient to demonstrate suitable relationships between affective state and a scale of cognitive capability, e.g. forming a level of perception. Splitting the data into two produced a subset containing low to medium values, of for example *level of activity,* and a second subset containing medium to high values of activity. The results showed that one of the subsets would demonstrate different, if not opposing, correlative relationship to the other subset. The majority of results explored suggested that a single slip to the data was required and therefore the opinion was taken that additional splits to the data were superfluous with little benefit to the process under development.

Table 3: Results from testing of classifier for *number of people*

Rule Set	Correctly Classified Instances	Coverage of cases (0.95 level)	Cross Validation Accuracy
class = user_selected	68.8889 %	77.7778 %	0.745875
	66.6667 %	75.5556 %	0.767327
	73.3333 %	77.7778 %	0.763476
	75.5556 %	77.7778 %	0.765677
	68.8889 %	75.5556 %	0.752475
If user_selected > 3 THEN class = 3 If user_selected = 3 THEN class = 2 If user_selected < 3 THEN class = 1	91.1111 % 93.3333 % 93.3333 %	100 % 97.7778 % 95.5556 %	0.927393 0.922442 0.925193
	95.5556 %	95.5556 %	0.924092
	84.4444 %	88.8889 %	0.926073
If user_selected > 3 THEN class = 2 ELSE class = 1	100 % 97.7778 %	100 % 100 %	0.960396 0.957096
	93.3333 %	95.5556 %	0.954895
	95.5556 %	95.5556 %	0.955446
	97.7778 %	100 %	0.957096

While all categories of context tested provided usable results, two aspects in the final experiment were implemented. The results of cycle three as presented in chapter five, section 5.4, identified level of activity as a key disruptive context which affected user behaviour so its inclusion was essential. Results also demonstrated that the level of distraction was also the most consistent context that

resulted in significant differences in behaviour. Therefore only level of activity and level of distractions were used in the final experiment as these two disruptive contexts, when used together, provided an accurate and repeatable profile from which to model user cognitive behaviour. Using additional disruptive contexts at this point would have added a level of complexity that would have made it potentially more difficult to analyse results, however this process should not be ruled out in following research as it will potentially give superior results.

Table 4: Results from testing of classifier for *amount of recent activity*

Rule Set	Correctly Classified Instances	Coverage of cases (0.95 level)	Cross Validation Accuracy
class = user_selected	42.8571 %	52.381 %	0.485714
	71.4286 %	80.9524 %	0.471429
	33.3333 %	71.4286 %	0.464286
	38.0952 %	66.6667 %	0.471429
	57.1429 %	66.6667 %	0.468571
If user_selected > 3 THEN class = 3 If user_selected = 3 THEN class = 2 If user_selected < 3 THEN class = 1	71.4286 %	85.7143 %	0.671429
	76.1905 %	80.9524 %	0.7
	61.9048 %	76.1905 %	0.707143
	85.7143 %	100 %	0.705357
	61.9048 %	85.7143 %	0.712857
If user_selected > 3 THEN class = 2 ELSE class = 1	71.4286 %	85.7143 %	0.814286
	71.4286 %	85.7143 %	0.810714
	85.7143 %	95.2381 %	0.82381
	76.1905 %	80.9524 %	0.821429
	85.7143 %	95.2381 %	0.81

4.5   Cycle Four

The last stage of this research involved a single experiment that drew upon the accumulation of results produced from the previous three cycles of work and focused upon a revision of the Android application developed as previously described in this chapter. The machine learning classification functionality was incorporated so that the application was able to determine levels of user physical activity and environmental disruptive contexts which then supported dynamic user engagement. The

final application implements methods for assessing both domains at the same time, i.e. both the user purchase-decision involvement and user perception questionnaire process. This, together with the contextual classification enables the system to identify whether the participant has a high or low likelihood of being involved in a purchasing decision and determine the best method of presenting the advert information in order to obtain a more effective method of purchaser engagement.

4.5.1 Predicting Levels of User Purchase-decision Involvement and Perception of Advertisements

In this final experiment the Android application, SiDISense, implemented a Java/Weka Backpropagation Neural Network algorithm that classified both accelerometer and audio data captured via inbuilt smartphone sensors. As mentioned previously the recording of private data is of ethical concern. To address this the SiDISense application extracted the required features from the data recorded and then applied the neural network classification algorithm. Once the instance of the survey was completed the initial recordings of data and the feature set files on the phone were then deleted. Section 4.4.3 describes the methods used in the identification of features and the development of routines used to classify data.

SiDISense utilised many key components developed in cycle three of the research. The questionnaires are implemented in the same manner and followed the initial hypothesis that straightforward interfaces are needed to ensure a user's continued engagement over multiple iterations of completing an application based survey. The results from the completed survey were subject to the AES-RSA encryption process described in section 4.4 before being uploaded to a secure server for later use and analysis.

Also as per experiment in section 4.4.1 a total of twenty-four high-involvement products were used in determining levels of user purchase-decision involvement and perception, including *houses, cars, computers, laptops, mobile phones, books for education, jewellery or watches, hotels, holidays, airline tickets, car insurances, life insurances, bicycles, televisions, hi-fi stereos, champagnes, washing machines, fashionable clothes, health care packages, cosmetics, sofa suites, fridge freezers,*

home broadband packages and *video streaming packages*. In the experiment the participant selected a single product from the list of product names. The product selected was then presented as a basic advert using either mental imagery or detail orientated processing writing styles. Both styles of advert for a particular product use the same unbranded image and the text for each was also limited to very generic, unbranded, product based information. The detail processing advert comprised of several short statements whereas the mental imagery advert comprised of fewer yet longer paragraphs written to induce the mental imagery process (see Appendix M for text and images used for each product used in the experiment). See figure 17 for the procedural structure of the application.

The key difference in approach to the previous two experiments was the inclusion of the classification function and the application of the system processes. SiDISense utilised background services to manage when the survey was run and also for managing the collection of accelerometer data. The classes used in this process are shown in the 'package', *backgroundService*, see program structure shown in figure 18. The main background service, (*ActivityService* class), manages the whole process of waking and then initiating the survey. The second background service, (*AccelerometerActivityService* class), manages the process of recording the accelerometer. Every five minutes the *AccelerometerActivityService* class wakes to determine whether the fifteen minutes of recording is in process, if not then the recording is initiated.

The main background service also wakes at five minute intervals (the two services are not in sync) to determine whether the survey has been completed recently and whether a recent batch of accelerometer data is available so that the survey can start. Note that the participant can set the frequency of survey completion via the management interface (*StartManagement* class). If the survey is in a position to start and the participant is using the phone, i.e. the screen is on, the service will ping the participant that the survey is ready and will wait for one minute of no engagement before resetting and starting the wait process once again.

If the participant opts to start the survey at this point the application will initiate the implementation of the survey questionnaires, all of which reside in the package called 'snapshot' as shown in figure 18.

At the same time the main background service will initiate the recording of the one minute of audio data on a separate thread. Once the recording is completed both the accelerometer and audio data have their feature sets extracted and the values of *physical activity* and *disruptions* are determined using the neural network classifier as implemented in the classes shown in the 'process' package, see program structure shown in figure 18.
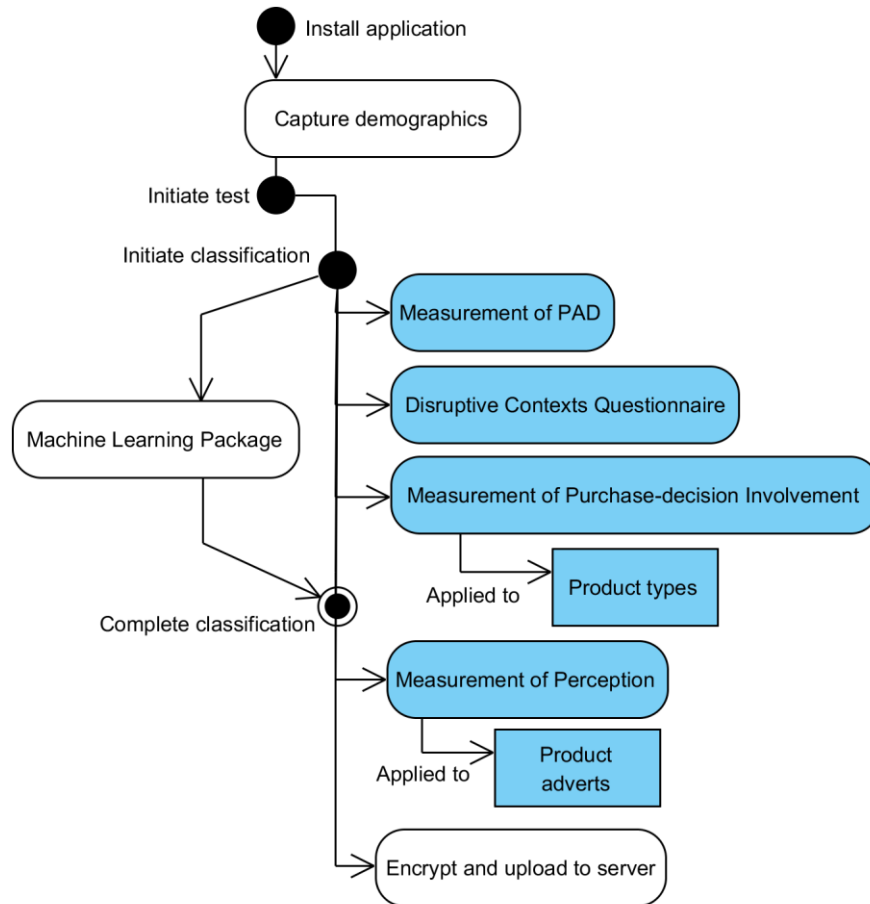
Figure 17: Purchase-decision Involvement and User Perception – Procedural structure of Android application

During the process of classifying the recorded data the participant will complete the initial parts of the survey, i.e. the PAD scale, the disruptive contexts, the product selection and the purchase-decision involvement questionnaires. The reader will note that the response from the participant regarding the disruptive contexts questionnaire is an overlap to the classification output. Continuing to capture the participant's input ensures that analysis of the success rate of the classification process is possible.
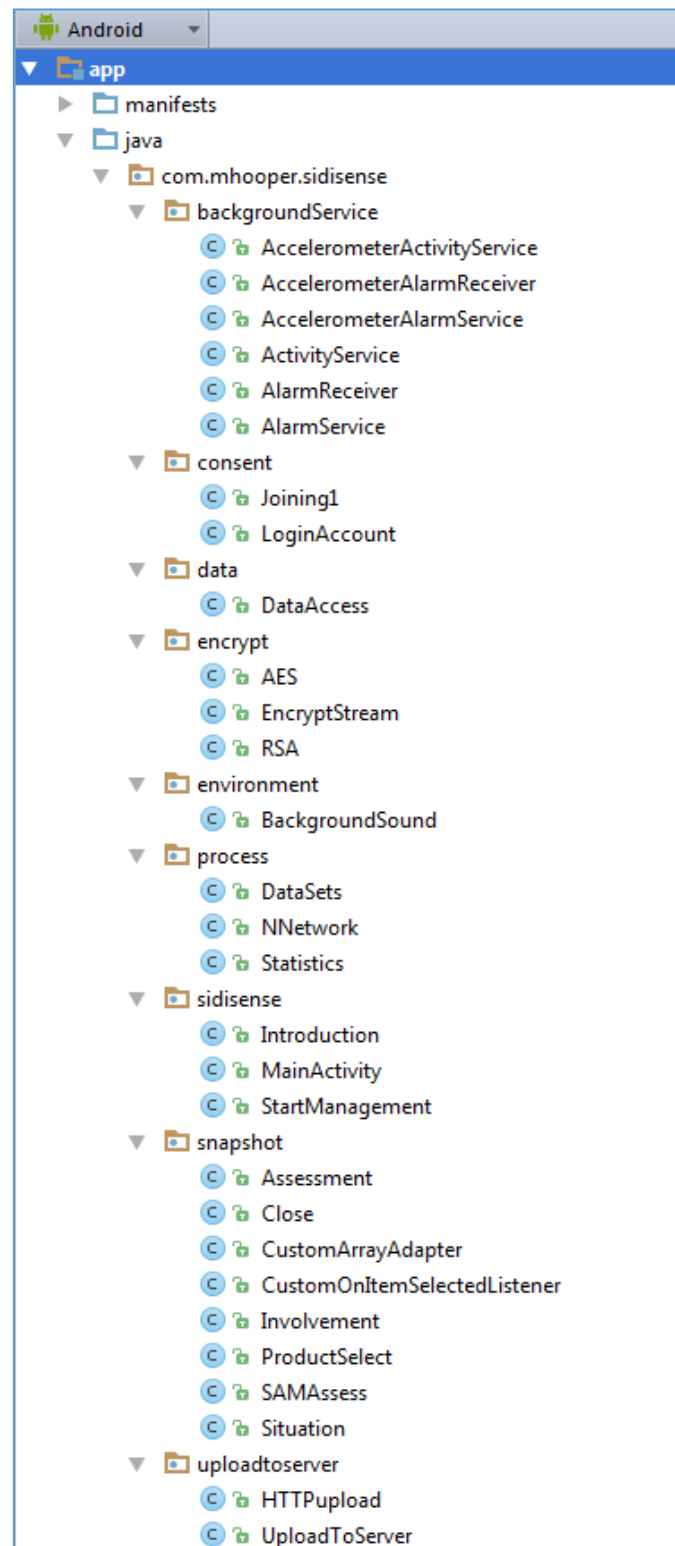
Figure 18: SiDISense application class structure

```java
boolean usingDetailProcessing = true;
boolean advertise = true;
int userCase = 0;
// Step 1
if (activity.equals("HIGH")) {
   if (user_dominance > 3) {
      // use detail processing
      userCase = 1;
   } else {
      // use mental imagery
      userCase = 2;
      usingDetailProcessing = false;
   }
} else { // low activity
   if (user_dominance > 3) {
      // using detail processing
      userCase = 3;

   } else {
      userCase = 4;
      // Neither detail processing or mental
imagery work well
      // do not advertise
   }
}
// Step 2
if (userCase == 1 || userCase == 2) {
   if (distractions <= 3) {
      // PDI is higher so advertise
      userCase = 5;
   } else {
      // PDI is lower so do not advertise
      advertise = false;
      userCase = 6;
   }
} else if (userCase == 3) {
   if (distractions > 3) {
      // Perceptions higher so advertise
      userCase = 7;
   } else {
      // Perceptions are lower so do not advertise
      advertise = false;
      userCase = 8;
   }
} else if (userCase == 4) {
   // Neither DP or MI work well
   // Perceptions are lower so do not advertise
   advertise = false;
}
```

Figure 19: SiDISense context-aware logic

On completion of the initial questionnaires the classification of accelerometer and audio data is also completed. At this point the system has elements of context-awareness and is then in a position to apply the logic detailed in figure 19 to determine a course of action for applying the final stage of the survey, i.e. measuring the user perception of the product adverts.

Before implementation of the final stage the system determines the most appropriate method of advert styling, i.e. mental imagery or detail processing. More importantly it also determines whether or not to advertise at all, for example if the level of purchase-decision involvement is low then the system will choose not to place an advert. This decision process is actioned using the logic in figure 19 which utilises the level of user dominance from PAD, the level of activity and the level of distractions to form the final decision.

To test the effectiveness of this approach the system ran on an alternating context-aware vs. static approach. The static approach ignored the classification of context and the inputs from the participant to simply always advertise the product using the detail processing approach to advert styling which is typical of simple m-commerce advertisements. The results and analysis of this approach are discussed in chapter five, section 5.5.

4.6   Chapter Summary

This chapter has covered in detail the implementation of the experiments conducted within this research. The research has been presented within four cycles that have clearly shown the development of the research effort. The first three cycles have each conducted two experiments, one focusing upon the domain of user purchase-decision involvement and the other focusing upon the domain of user perception. The final cycle consisted of one experiment which focused upon both domains to demonstrate a process of engagement with the user that not only considered involvement with a product but also the perception of the product information presented via a mobile device.

Each cycle of experiments built upon the previous cycle's results. Initial work implemented both a paper based survey and a basic android application. Findings led to a second iteration of experiments

which utilised Google Forms, which in turn then led to a bespoke Android application being developed for use in the third and the fourth cycles' experimentation. The outcomes from the two Google forms surveys directed the development of the Android application, SiDISense. This software implemented almost identical versions of the instrumentation used previously but also delivered the ability to engage with the participant multiple times and utilised a smart-phone device's built in sensors for collecting data that could be used to develop automatic classification routines. The microphone and the accelerometer were used to record data which was then categorised by the participant into levels of disruption and activity respectively. Each version of the labelled data was reduced to a feature set which not only ensured privacy but also supported the development of a classification routine that would be implemented within the final iteration of the research.

Even though the implementation method of the survey developed over the four cycles, i.e. paper-based through to Android application, the use of the instrumentation within remained relatively static. For each experiment detailed in this chapter a structure diagram is provided to demonstrate the instrumentation used. The main significant changes to the overall survey were the concatenation of the two domains of focus and the development of the disruptive contexts questionnaire which developed into a six point questionnaire but which was then later shortened to a smaller subset to reduce the perceived burden upon the participant.

In section 4.4.3 describes the Machine Learning classification method followed for training of data to identify different levels of specific contexts. This section started with the identification and extracting of feature sets that would enable real-time processing of microphone and accelerometer data, and finishes with the classification results that formed the decisions in the development of the final version of the application. In order to produce a suitable classification routine a Java application that implemented a set of Machine Learning libraries called Weka was developed. A Backpropagation Neural Network function was trained using the labelled data feature sets to identify levels of noise, distractions, number of people and amount of activity. This functionality was then transferred to Android for use within the last version of SiDISense to demonstrate a level of context awareness that

could be used to support the correct level of user engagement to follow when attempting to apply product placements via a mobile device.

Table 5: Chapter four and five corresponding sections pairing

Chapter Four		Chapter Five	
Section number	*Section title*	*Section number*	*Section title*
Cycle one		*Cycle one*	
4.2.1	An Investigation into Perception of Textual Presentation Styles	5.2.1	Textual Presentation Styles and User Perception
4.2.2	Initial Study of User Involvement	5.2.2	User Purchase-Decision Involvement relationships
Cycle Two		*Cycle Two*	
4.3.1	Exploring the Effects of Situational Contexts on User Perception of Advertisement Styles	5.3.1	Effects of Situational Contexts on User Perception of Advertisement Styles
4.3.2	Exploring the Effects of Situational Contexts on Purchase-Decision Involvement	5.3.2	Effects of Situational Contexts on Purchase-Decision Involvement
Cycle Three		*Cycle Three*	
4.4.1	Categorizing User Perceptions of Advertisement Styles within Disruptive Contexts	5.4.1	User Perceptions of Advertisement Styles within Disruptive Contexts
4.4.2	Categorizing Levels of User Purchase-Decision Involvement within Disruptive Contexts	5.4.2	User Purchase-Decision Involvement within Disruptive Contexts
Cycle Four		*Cycle Four*	
4.5.1	Predicting Levels of User Purchase-Decision Involvement and Perception of Advertisements	5.5.1	Success in Predicting Levels of User Purchase-decision Involvement and Perception of Advertisements

The following chapter presents the results and analysis of all the findings from the above experiments, including the use of neural network classification of context in the final implementation of the Android application. Chapter five is presented in the same cycle-experiment structure as chapter four, in other words the experiment described in a subsection of chapter four has a corresponding results and analysis section in chapter five. The link between the contents of the two chapters is presented in table 5 where the two chapter's corresponding section numbers and section titles are paired.

5. Analysis and Results

5.1 Introduction

This chapter presents and analyses the results from all the experiments detailed in the Implementation of Research chapter discussed earlier, see chapter four. The structure of the chapter follows the outline of the previous chapter where each set of results is presented within the cycles of research, from one to four. Each cycle contains the results of two experiments except for the fourth cycle which is a concatenation of the previous work into a single experiment.

As a whole, the research attempts to demonstrate its primary hypothesis by showing how the use of context-awareness can improve the effectiveness of user engagement where m-commerce recommender systems are attempting to convert a browser to a purchaser. Each of the following sections in this chapter discuss supporting hypotheses that lead to the fulfilment of the main hypothesis in the final experiment.

All the experiments involved are survey based and utilise a number of self-administered questionnaires; the reasoning for taking this approach is explained in chapter three. The surveys are administered in different ways depending upon the requirements of the experiment and the development of the research hypothesis. These range from paper-based, laboratory implementation, on-line Google Forms and finally a bespoke Android smart-phone application that uses Artificial Intelligence to classify levels of disruptive context within the participant's own in-the-wild situations. The instrumentation used within the questionnaires are either existing tools or tools being developed for the purpose of this research; chapter three discusses these in detail. Early on in the iterations of the research cycles the structure of the survey is established and adhered to throughout, with only minor changes as required for implementation. The previous chapter, chapter four, discusses the implementation of each experiment, providing details of the use of tools and the overall process of user-survey engagement.

To ensure clarity in the presentation of the analysis and experimental results, the following elements with be considered throughout this chapter:

(a) Describe the data sample

(b) Reiterate the hypotheses being tested, noting changes (if any) between cycles of research

(c) Discuss what each experiment expected to achieve from the analysis of the data collected

(d) Discuss any significant results and consider issues that led to insignificant outcomes

(e) Highlight trends and analysis outcomes

(f) Provide hypothesis confirmation, non-confirmation or partial confirmation

The chapter summary will then consider all the results achieved in the research effort, discussing the responses to the hypotheses developed before introducing the main discussion within chapter six.

5.2 Cycle One Results

5.2.1 Textual Presentation Styles and User Perception

This Android application implemented survey collected 57 responses with 58% of responses completed by male participants. A total of sixteen users participated in the experiment, 75% male and 25% female. Though a wide ethnic population was included 62% were white British. The spread of age groups were as follows, 21 years and under (25%), greater than 22 years and less than 35 years (50%), greater than 35 years (25%). Files demonstrating the analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-i).

Though strong correlative results were sought it was obvious to not expect perfect values for either positive or negative correlations for the following reasons. The main issue lies with the self-reporting technique used in the data collection. Firstly the user's input is subjective, relying upon the user's emotional intelligence (ability to self-assess their mood and emotions). Secondly, both the input for the PAD assessment and all the perception feedback both utilize the Likert style scales which can be

prone to central tendency bias especially when cognitive load is high (Allred, Crawford, Duffy, & Smith, 2016).

This experiment involved a primary hypothesis where it was expected that by determining a user's affective state as being positive it would be possible to establish a different set of likely behaviours when compared to a negative state. In other words understanding these behaviours should provide insight into how a user's affective state affects user perception of textual statements presented via a mobile device. This notion would then support the development of a context aware system for use within e-commerce. If such a system was able to determine how a user would perceive product information then its efficiency, in terms of consumer engagement, would improve considerably. To investigate this a number of hypotheses were pursued that together will represent a broad understanding of user perception (and thus potential user behaviour) for use with context-aware systems.

Processing Style

*H*1a: *that a positive correlation will be achieved between user affective state and the perception of a mental imagery inducing statement*

*H*1b: *that a negative correlation will be achieved between user affective state and the perception of a statement using analytical, detail-oriented reasoning*

Risk Acceptance

*H*2a: *that a positive correlation will be achieved between user affective state and the perception of a statement with a low risk focus*

*H*2b: *that a negative correlation will be achieved between user affective state and the perception of a statement with a high risk focus*

Cognitive Capacity

*H*3a: *that a positive correlation will be achieved between user affective state and the perception of a statement with low effort processing*

H3b: *that a negative correlation will be achieved between user affective state and the perception of a statement with more effortful processing*

Appeal Type

H4a: *that a positive correlation will be achieved between user affective state and the perception of an optimistic appeal statement*

H4b: *that a negative correlation will be achieved between user affective state and the perception of a fear appeal statement*

As the hypotheses are biased towards particular positive or negative correlations one-tail correlation was tested for, the results of which are represented as *r*. The probabilities of these are measured using *p-values* and where statistically significant are shown as $p < .05$ (confidence level of 95%) or $p < .01$ (confidence level of 99%).

The results are as follows. A positive correlation between level of affect and the perception of mental imagery statements ($r = .45, p < .01$) is found, thus I am able to reject the null hypothesis for *H1a*. However it is not clear that the opposite case applies i.e. a negative correlation between affect and the perception of analytical detail processing. There results show a minor, insignificant correlation, thus I fail to reject the null hypothesis for *H1b*.

The failure of *H1b* could be explained by suggesting that though detail processing is favoured when in a negative state, it may not be true that we are unable to undertake analytical processing when in a positive state. Though the undertaking of mental imagery may 'take up' cognitive capacity and thus reduce detail processing it does not necessarily mean that there is an inability to conduct some detailed analytical processing in the absence of mental imagery processing.

For *H2a* a positive correlation between level of affect and the perception of low risk statements is fount, therefore I can reject the null hypothesis for *H2a* ($r = .3, p < .05$). However the results present no significant correlation between affect and the perception of high risk statements, thus I fail to reject the null hypothesis for *H2b*. This lack of correlation could be due to the levels of complexity in the

different types of negative emotions. For example the negative emotions of anger and fear have opposing effects, with angry people favouring risk and fearful people being more risk adverse. This demonstrates that the other axis of PAD i.e. arousal and dominance could be also required when exploring specific presentation styles. I should also acknowledge that other contexts could be having an effect on mobile device users' perception of risk. User environment and activity could be having an impact on their capacity to process information especially if the message requires careful deliberation.

The hypotheses applied to perceptions of effort follow a similar pattern to *H1* and *H2*. A relatively low positive correlation ($r = .28, p < .05$) has been found between user affective state and the perception of a statement with low effort processing. However no useful correlation is present between user affective state and the perception of a statement with more effortful processing. Therefore I can reject the null hypothesis for *H3a* but not *H3b*. While I expected participants in a negative emotional state to be more favourable towards higher processing effort, it is possible that problematic situations and therefore additional knowledge of a user's situation and its effect upon cognitive capacity could be key to understanding the lack of correlation in hypothesis *H3b*.

The pair of hypotheses, (*H4a, H4b*), which involved both optimistic and fear appeals are also only partly validated. The expected positive correlation between user affective state and the perception of an optimistic appeal statement was successfully achieved ($r = .45, p < .01$) and I can reject the null hypothesis for *H4a*. The results for the perception of fear appeal statements, as expected, produced a negative correlation, however, potentially due to a small dataset, no significance is found and therefore I am unable to reject the null hypothesis for *H4b*.

For this experiment's four hypotheses I see only a partial confirmation where positive correlations are achieved between statements that include *mental imagery, low risk, low effort and optimistic appeals* and the positive-negative axis of user affective state. As no significant negative correlations were achieved between positive-negative affective state and the statements that included *detail processing, high risk, high effort* and *fear appeals* it was important to consider the following. Firstly, as these four message styles failed to produce a positive correlation, it is likely that the user uses different cognitive

processing when compared to how they are processing those message styles that did produce positive correlations. Secondly, as the expected negative correlations were not achieved, the result can suggest that either negative affective state is far more complex than positive affective state or that these phenomena are more likely prone to situational differences that could also hinder cognitive ability. Because of the nature of this research I focus upon the latter and explore further the effect of situational contexts upon user behaviour.

These findings are important in that if a recommender system is armed with values for affective state then it can determine how best to present the recommended item by using one of the mental imagery, low risk, low effort and optimistic appeals styles. For example irrespective of the product being recommended, if the user is in a positive state the system could use mental imagery to maximize purchase conversion rates, and when negative, it could use different techniques such as increasing brand awareness or product comparisons. Understanding how a user's mood shapes their response to risk also potentially enables a system to determine how and when to present certain higher risk items, for example an expensive holiday.

5.2.2 User Purchase-Decision Involvement relationships

This small survey collected 49 responses with 76% of responses completed by male participants. The spread of age groups were as follows, 21 years and under (39%), 22 to 34 years (57%), 35 to 45 years (0%), greater than 45 years (2%) and 2% unknown where the form was not fully completed.

Following the previous experiment I explore the notion that additional situational contexts impact upon correlations between user affect and certain cognitive processes. Previous research has demonstrated that positive correlations exist between the pleasure axis of the PAD scale and the purchase-decision involvement scale (PDI). Several social contexts are explored and note their effect upon this positive correlation noted.

As discussed in chapter two, section 2.6.2, I identify that high levels of certain contexts will impact upon user cognitive capability. A number of disruptive contexts were highlighted, including noise

(Guski et al., 1999) and distractions (McGehee, 2014), that can affect both behaviour and the evaluative aspects of cognition. I therefore developed hypotheses based upon this understanding.

H5a: high levels of unfamiliarity in both location and people contained within that location will increase the positive correlation between user affective state and purchase-decision involvement

H5b: high levels of user activity will increase the positive correlation between user affective state and purchase-decision involvement

H5c: high levels of noise will increase the positive correlation between user affective state and purchase-decision involvement

H5d: high levels of user engagement will increase the positive correlation between user affective state and purchase-decision involvement

As the dataset is small I test the hypotheses using both one-tailed and two-tailed probability to assess any correlations in the results; these are represented as *r*. The probabilities of these are measured using *p-values* and where statistically significant are shown as *p < .05* (confidence level of 95%) or *p < .01* (confidence level of 99%). The analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-ii).

The key findings are presented in table 6 which shows the highest correlation between high or low values for each context. For example the level of noise was tested for both low and high values (note the scale used was between one and seven). It is possible to see that low *familiarity of your immediate environment* and low *familiarity with people in your immediate vicinity* both increased the positive correlation. This demonstrates that increased unfamiliarity will have more effect upon someone in a negative state than in a positive state. The results show an increase in the correlation produced when the value is low for the category of *how comfortable do you feel in your current surroundings?* This provides additional weight to the result discussed above, that levels of unfamiliarity and level of confidence are related. From the above I can reject the null hypothesis for *H5a*. The results for high levels of noise in the environment also provide evidence that an increase in the positive correlation

between affective state and PDI is achieved, therefore I can also reject the null hypothesis for *H5c*. A high level of user activity did produce an increase as expected, however due to insignificant values in probability I fail to reject the null hypothesis for *H5b*.

Table 6: The effect of context upon the positive correlation between user affective state and purchase-decision involvement

Context	*Value*	*Correlation*	*One-tailed probability*	*Two-tailed probability*
All data	N/A	0.38	< .01	< .01
Familiarity of your immediate environment	< 5	0.46	< .05	< .05
Level of noise in your immediate environment	> 4	0.51	< .05	> .05
Your amount of activity within the last couple of minutes	> 5	0.44	> .05	>.05
How comfortable do you feel in your current surroundings?	< 5	0.62	< .05	< .05
Number of people in your immediate vicinity	< 4	0.56	< .05	< .05
Familiarity with people in your immediate vicinity	< 4	0.67	< .001	< .05
Current level of engagement / interaction with people in your immediate vicinity	< 4	0.63	< .05	< .05

To test the final hypothesis in this experiment the categories of *number of people in your immediate vicinity* and c*urrent level of interaction with people in your immediate vicinity* are assessed. Surprisingly both of these contexts produced increased correlations between user affective state and PDI when the values were low. From the hypothesis I expected that context of user engagement would produce the same results as noise i.e. both being disruptive to the cognitive process, however where fewer people and less engagement reduces the level of PDI when in a negative state this suggests that solitude and negativity do not inspire cognitive processes in a positive way. From this result I am unable to reject the null hypothesis for *H5d*.

While some of the results from this experiment were as expected, some were not. I have already suggested that negative state and solitude could be a reason for the failure of proving that high

engagement has the effect expected, however also considered should the nature of the experiment's implementation. As this was a paper-based survey within a relatively controlled setting where all the participants were sitting in relatively quiet surroundings it is possible that this influenced the perception of their environment and also limited the level of 'high' responses to the questions. It is possible that this reason also influenced the responses to the level of activity question. As the participants were sitting while waiting to start and when completing the questionnaire this may have impacted upon the influence that was expected to a high level of activity.

These results influence the design and implementation of the following experiments which were accessed on-line by the participant in their preferred environment and using their preferred device. This in-the-wild approach forms the basis of the rest of the research conducted hereon.

5.3   Cycle Two Results

5.3.1   Effects of Situational Contexts on User Perception of Advertisement Styles

While this experiment focuses on only a single high-involvement product (a smart-phone) encouraging results are seen which suggest that the *eab-perception* scale is suitable for feedback capture from a mobile device user. In this experiment 169 responses are collected with 53% completed by female participants. The age groups were as follows, less than 22 (5%), 22-34 years (37%), 35-45 years (29%), greater than 45 years (29%). The files showing the analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-iii).

Results from the previous cycle's experiments suggested that some situational contexts impact upon correlations between user affect and certain cognitive processes. I have already confirmed that a positive correlation exists between the pleasure-displeasure axis of the PAD scale and the purchase-decision involvement scale. This is extended by applying this theory to different advertisement presentation styles of detail processing, mental imagery and fear appeal. I also investigate whether different contexts also impact on these relationships.

The hypotheses developed assume that high values for the contexts measured will impact more on the user when they are in a negative state, therefore the following are proposed:

H6a: *positive correlations between user positive-negative affective state and different advertising styles exist when assessing high-involvement products*

H6b: *high levels of unfamiliarity in both location and people contained within that location will increase the positive correlation between user positive-negative affective state and the different advertising styles*

H6c: *high levels of user activity will increase the positive correlation between user positive-negative affective state and the different advertising styles*

H6d: *high levels of disruptions (i.e. noise, distractions) will increase the positive correlation between user affective state and the different advertising styles*

H6e: *high number of people will increase the positive correlation between user positive-negative affective state and the different advertising styles*

In this experiment two-tailed probability is tested for; results are represented as *r*, the probabilities of these are measured using *p-values* and where statistically significant are shown as $p < .05$ (confidence level of 95%) or $p < .01$ (confidence level of 99%).

The results of this experiment show that the complete dataset produces a relatively low, yet significant, positive correlation between affective state and detail processing ($r = 0.22$, $p < .01$) however only near to zero, insignificant, correlations with mental imagery and fear appeal are produced. Splitting the data between the smaller devices (smart-phone and tablet), and larger devices (PC and laptop), provided suitable datasets to analyse further. Surprisingly there is no significant correlations in the non-mobile data set for any of the different processing styles. However significant correlations are found for both detail processing ($r = 0.41$, $p < .01$) and mental imagery ($r = 0.28$, $p < .05$) in the mobile dataset, see table 7 for detailed results.

As users of larger, static devices are showing no evidence of correlations for any processing styles this suggests that the environment we associate these devices with is not impacting upon users' cognitive processing capability and affective state relationships. The figures associated with these devices skewed the overall results, however their removal from the dataset demonstrates that users of mobile devices are showing a relationship between affective state and processing styles, for example detail processing produces a significant correlation of $r = 0.41, p < .01$. This suggests that the variance in the mobile user's environment is impacting on their cognitive capability and that environmental contexts are producing interesting relationships that could be modelled within a computing system. The above is an interesting point to consider as this result means I can only reject the null hypothesis for *H6a* for smaller mobile devices, which in itself provides evidence to support further development of the hypotheses that will be more context focused.

Table 7: Correlations for detail processing and mental imagery and fear appeal

	Detail analysis		Mental Imagery		Fear appeal	
Context	*result*	*P*	*result*	*p*	*result*	*P*
All devices	0.22	< .01	0.001	> .05	0.07	> .05
All mobile devices	0.41	< .01	0.28	< .05	0.24	> .05
All other devices	0.1	> .05	-0.18	> .05	-0.06	> .05

Even when additional contexts are used to split the data i.e. high noise, there is little change in the correlation levels of the non-mobile data. The only notable exception is where the split for *level of activity* is applied to the non-mobile data. Where the level is greater than four out of seven a negative correlation for all three presentation styles is seen, with the largest being for the mental imagery advert (r -0.42, $p < .05$). These results provide additional evidence that users can behave differently depending on the device they are using and that context needs to be the focus of study to ensure that m-commerce is successful.

Using the mobile only dataset (a reduced set of 66 instances) the hypotheses above were addressed by applying data splits to produce smaller datasets that focus upon higher levels of particular contexts,

i.e. select all higher levels of distraction responses greater than three out of seven and apply the correlation test. Table 8 presents the results from these context focused correlation tests. From the results I can state that higher levels of noise ($r = 0.54$, $p < .01$), distractions ($r = 0.52$, $p < .01$) and familiarity with people in immediate vicinity ($r = 0.5$, $p < .05$) all increase the correlation between the pleasure dimension and the detail analysis presentation style. Similarly I can state for both the presentation styles of mental imagery and fear appeal that there is some evidence that correlation values can increase by a larger degree than for detail analysis. However there is also some evidence that in some cases the opposite seems to be true, for example for both elements of familiarity, i.e. people and environment, there is a substantial decrease in the correlation values when using fear appeal, $r = 0.07$, $p > .05$ and $r = 0.13$, $p > .05$ respectively.

Higher levels of activity also did not produce the values expected. While the use of mental imagery did produce a substantial increase in the correlation result from $r = 0.28$, $p < .05$ up to $r = 0.5$, $p < .05$ the other presentation styles of detail processing and fear appeal show a decrease in the correlation assessed. This result provided the first insight into the importance of physical activity in the forming of perceptions and other cognitive function. In other words where high and low activity values, when paired with other disruptive context, produce different values in correlative relationships. The importance of user activity becomes a focus within cycle three of this research where the contextual models are developed, see section 5.4.

From these results it is possible to see that in some cases, e.g. level of distractions, an increased amount of certain contexts will demonstrate an increased correlation between the dimension of positive-negative affective state and different advertising styles. Detail processing ($r = 0.52$, $p < .01$), mental imagery ($r = 0.4$, $p < .05$) and fear appeal ($r = 0.51$, $p < .01$) all produced a positive increase where the level of distraction was high. However while this evidence exists it is not across all instances and I am therefore not able to reject the null hypothesis for *H6b*, *H6c or H6d*. I also find the results concerning unfamiliarity were insignificant and therefore I also fail to reject the null hypothesis for *H6e*.

Table 8: Correlations for detail processing, mental imagery and fear appeal

		Detail analysis		Mental Imagery		Fear appeal	
Context	*Value*	*result*	*p*	*result*	*p*	*result*	*p*
All mobile devices (smart-phones/tablets)	ALL	0.41	< .01	0.28	< .05	0.24	> .05
Level of noise in your immediate environment	> 3	0.54	< .01	0.4	> .05	0.44	< 0.05
Amount of distractions in immediate vicinity	> 3	0.52	< .01	0.4	< .05	0.51	< .01
Current (or very recent) level of physical activity	> 3	0.26	> .05	0.5	< .05	0.18	> .05
Number of people in immediate vicinity	> 1	0.38	< .05	0.36	< .05	0.3	> .05
Familiarity with people in immediate vicinity	< 6	0.5	< .05	0.33	> .05	0.07	> .05
Familiarity of immediate environment	< 5	0.44	> .05	0.04	> .05	0.13	> .05

It is probable that the smaller sized dataset contributed to making it difficult to prove these hypotheses. Addressing individual contexts is also not a realistic approach and is an issue, this is addressed in later experiments by pairing contexts together. In addition to this, the experiment only focuses upon a single product, the smart-phone, and this may be the cause of the inability to confirm or reject the null hypotheses above. There is also the issue of providing consecutive adverts all focused upon a single product, even though of different styles, to consider. This most likely led to the participants' lack of focus or pre-conceptions being developed from one advert to the next, therefore skewing any feedback given. A number of points however are identified that will benefit further experiments. Most importantly it has been shown that users interact with their mobile devices differently to their larger devices, with only smart-phones and tablets producing a statistical significance relationship between user level of pleasure and their perception of different processing styles. Also found is that some situational contexts also increase the significance of this relationship, in particular where small devices are used but not necessarily to the same level for all information

processing styles. These findings help redefine the hypotheses used with the later experiments within this project, which will focus upon mobile devices and specific situational contexts.

5.3.2 Effects of Situational Contexts on Purchase-Decision Involvement

This experiment aims to demonstrate that the relationship between a user's positive mind-set and purchase-decision involvement is affected by contexts that are negative to a situation. Levels of noise, distractions, activity and unfamiliarity with the environment are all investigated further and their impact reported.

A total of 140 responses were taken with 53% of responses completed by male participants. The spread of age groups were as follows, 21 years and under (8%), 22 to 34 years (38%), 35 to 45 years (23%), greater than 45 years (31%). In this experiment two-tailed probability is tested for; results are represented as *r*, the probabilities of these are measured using *p-values* and where statistically significant are shown as $p < .05$ (confidence level of 95%) or $p < .01$ (confidence level of 99%). The files showing the analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-iv).

The hypotheses developed for this experiment focus on *unfavourable* contexts and their impact upon the relationship between user positivity and purchase-decision involvement:

*H*7: *Individual physical contexts will not have a direct correlation with positive-negative affective state*

*H*8: *Individual environmental and behavioural stressors will show an increased level of positive correlation between positive-negative affective state and purchase-decision involvement*

*H*9: *An increased level of positive correlation between positive-negative affective state and purchase-decision involvement will be achieved when we are subjected to unfamiliar contexts (people and/or environment)*

*H*10: *An increased level of positive correlation will be achieved between positive-negative affective state and purchase-decision involvement when we are subjected to an unfavourable physical situation*

The results are as follows. After analysis of each of the six physical/social contexts it was found that none have a significant correlation with positive-negative affective state. Therefore for the individual contexts addressed in this test I can reject the null hypothesis for *H7*.

The correlation results for the five products are all very similar, so to reduce repetitiveness and confusion I report the average of the five products in the results that follow. Averaging of results across groups not only simplifies a process of representing results but is also useful in that it reduces the effect of random fluctuations and thus ensures the reliability of the data. I am not aware of any systematic bias associated with any of the individual products as they are all of similar 'type' and focus of the measure is known (Wiliam, 2000), i.e. 'high involvement products' and measurements of 'involvement'. Not only has the analysis not found any traits that suggest that specific product or service types help form different relationships, e.g. electronic goods, but rather it is the opposing influence between high and low involvement products that have been shown to produce variance in results (Yeh & Lin, 2010). However it has also been shown that data containing both high and low involvement products may lead to a lower result than if the focus was solely on high involvement products (Holmes et al., 2014). I therefore posit that averaging will not affect validity of the results.

The next step in the analysis was to confirm that there is a relationship between positive-negative affective state and purchase-decision involvement (PDI). The results show a positive correlation ($r = 0.2$, $p < .05$) for the complete dataset and even though the correlation is relatively low I can suggest that this supports Hansen's (Hansen, 2005) hypothesis that people prefer to make purchase decisions when based on positive motivation.

In addressing *H8* and *H9*, the analysis primarily presents zero correlations, but then trends of increasing correlations are found as the dataset is split for testing contexts at more extreme values. For *H8* high values are found for individual contexts of noise, distractions and number of people provide significant increases in the correlation between PDI and the positive-negative dimension of affective state (see table 9). Also shown is that a low level of physical activity will increase the relationship to $r = 0.49$, $p < .01$. While a high level of physical activity would be considered a behavioural stressor was

expected the opposite appears to be forming the correlative relationship between PDI and positive-negative affect. This suggests that while physical activity is a stressor to a person in the physical sense it is the low level of activity which is having an impact on cognitive behaviour. This is potentially an indicator that the person's negative mood is more effectual in impacting upon the cognitive capability in forming a level of PDI when the person is inactive, however it is impossible from this experiment to determine the cause of this effect fully. These results are all considerable increases from the full dataset correlation result of r = 0.2 and in view of this increase I can state that the null hypothesis for *H8* can be rejected for the environmental and behavioural stressors considered.

Table 9: PDI correlations for individual contexts

Context	*Value*	*result*	*p*
Level of noise in immediate environment	> 5	0.94	< .01
Amount of distractions in immediate vicinity	> 5	0.47	< .05
Current level of physical activity	< 2	0.49	< .01
Number of people in immediate vicinity	> 2	0.41	< .01
Familiarity with people in immediate vicinity	< 4	0.57	< .01

It was found that as an individual context *familiarity of environment* provides no useful increase in correlation and is not shown in table 9. However as familiarity of people does produce a significant result I fail to fully reject the null hypothesis for *H9*.

To test hypothesis *H10*, i.e. the impact of unfavourable physical situations, contexts are paired up to produce logic that extract two contexts of specific values e.g. high level of distractions partnered with low level of activity. These are then tested for correlations between affective state and PDI. By pairing contexts there is a concatenation of the effects of more than one context to demonstrate a 'disruptive situation'. While this by no means captures the full situation its aim is to demonstrate that multiples of disruptive contexts can have more influence upon the mobile device user's cognitive processes.

This exercise is completed for two main groups, 1) *distractions* and 2) *familiarity*. For the first exercise specific contexts were paired with *level of distractions*. Data with high distractions i.e. above 5 out of 7 are extracted and then an additional focus to copies of this data is applied by extracting either high or low values for *level of activity*, *level of noise* and *number of people,* as shown in table 10. All three dataset pairings produced significant correlations between PDI and the PAD pleasure dimension. The correlations produced are also greater than the correlations for the individual context data for high level of distractions which produced a starting correlation of $r = 0.47$, $p < .05$. Most noteworthy is the pairing of high distractions and low activity which produced a strong and significant result ($r = 0.73$, $p < .05$), but this result also adds further weight to the discussion based upon table 9 which considers the notion that a person's negative mood is more effectual in impacting upon the cognitive capability when the person is inactive. In addition to this it is possible to also suggest that this effect is increased as environmental disruptions increase. Also as expected there is a demonstration of two environmental disruptive contexts with high values, in this case *distraction* and *noise*, which when paired produce a high, significant increase in the correlative result ($r = 0.71$, $p < .05$).

Table 10: PDI correlations for contexts combined with level of distractions

Context (1st)	Value	Context (2nd)	Value	result	P
distractions	> 5	activity	< 3	0.73	< .05
distractions	> 5	noise	> 4	0.71	< .05
distractions	> 5	number of people	> 4	0.56	< .05

The second exercise using paired logic focuses upon familiarity (see table 11 and table 12). The first two pairs start with a dataset for *familiarity of people* as indicated by the user as less than 4 out of 7, with a secondary focus of both *familiarity of environment* and then *number of people*. The initial data split for *familiarity of people* produced a result of $r = 0.57$, $p < .01$, so the pairing with secondary contexts only produced minor increases in correlation i.e. *familiarity with environment* ($r = 0.64$, $p < .05$) and *number of people* ($r = 0.66$, $p < .05$). It is interesting however to observe that while

individual context *familiarity with the environment* produced no initial correlation, it does once paired with *familiarity of people*, with a result of $r = 0.64$, $p < .05$. While this is a small increase it potentially demonstrates that an unfamiliar environment may not be an issue in itself, however if physical stressors are in place then they become accentuated. This notion is discussed further in the following paragraph where further results of contextual pairings are observed (see table 12).

Table 11: PDI correlations for contexts combined with levels of familiarity of people

Context (1st)	Value	Context (2nd)	Value	result	p
familiarity of people	< 4	familiarity with environment	< 7	0.64	< .05
familiarity of people	< 4	number of people	> 2	0.66	< .05

Table 12: PDI correlations for contexts combined with level of activity

Context (1st)	Value	Context (2nd)	Value	result	p
familiarity of people	< 5	activity	< 3	0.76	< .01
familiarity with environment	< 7	activity	< 4	0.4	< .05
familiarity of people	< 5	activity	> 4	-0.56	< .05
familiarity with environment	< 7	activity	> 4	-0.58	< .05

The pairing of familiarity contexts are explored further by producing sub dataset splits using high and low levels of user activity (see table 12). In some cases the inclusion of activity affected the correlations produced by familiarity in an unexpected manner. Not only were there increases in correlations when there were low levels of activity, but where high levels of activity were present an unexpected reversal of correlations took place. As hypothesised it was found that with lower levels of activity, both familiarity of people and environment produces an increase in positive correlation, $r = 0.76$, $p < .01$ and $r = 0.4$, $p < .05$ respectively. Remember that familiarity with environment does not produce any correlation when assessed by itself. Of more interest is where contexts of familiarity, when paired with high levels of activity, produce negative correlations, for example pairing low familiarity of people and high activity produces a significant negative correlation of $r = -0.56$, $p < .05$.

While high activity was unable to show a significant correlation when described as an individual context it does appear to have influence when levels of familiarity are low. The reason for this effect is not immediately apparent but there is a strong reversal in cognitive behaviour depending on the level of physical behaviour. In other words it is where there is low familiarity and high activity that low PDI is formed when the person is in a positive state. This could be due to the person being unwilling to undertake particular cognitive behaviours because they are perhaps focused on the 'activity' and are aware of the 'unfamiliarity' of their environment, or the effect of high activity could be a cause of disengagement from decision involvement as the user focuses preference on tasks with lower cognitive requirements.

From the above it is possible to declare that combinations of context can produce an increase in correlation, positive or negative, and therefore I can reject the null hypothesis for *H10*. These results are novel and provide an interesting insight into the importance of user activity when preparing a context-aware system that focuses upon cognitive capability. This is explored further in the remainder of this section and in the subsequent research cycles.

As a further test to the hypotheses above a split to the data is applied so that a focused dataset produced for just smart-phones and computer tablets, i.e. smaller and truly mobile devices. This produced a much smaller dataset of just 71 instances. Unlike the complete dataset, which produced a positive correlation between positive-negative affect and PDI ($r = 0.2$, $p < .05$), the focused dataset produced no correlative result. Extending this also seen is that there is no correlation produced between PDI and arousal-nonarousal or the dominance-submissiveness affective state dimensions (see table 13).

This surprising result highlighted a possibility that mobiles device users were forming different relationships between PDI and affective state. This is explored by applying additional contextual splits, however due to the relatively small size of the focused dataset it is difficult to demonstrate any significant correlation. To overcome this the paired splits method is used again to demonstrate fully the effect that disruptive contexts were having upon the correlative relationships being formed.

Table 13: PDI correlations for combined contexts for only small mobile device data

Context (1st)	Value	Context (2nd)	Value	Pleasure		Arousal		Dominance	
				results	p	results	p	results	p
ALL data (smart-phone and tablets)				-0.02	> .05	-0.03	> .05	0.07	> .05
Activity	< 4	distractions	> 4	0.07	> .05	0.21	> .05	0.60	< .01
Activity	< 4	familiarity of people	< 6	0.23	> .05	0.07	> .05	0.64	< .05
Activity	< 4	Noise	> 2	-0.12	> .05	0.01	> .05	0.48	< .01
distractions	> 2	Noise	> 3	-0.01	> .05	-0.21	> .05	0.48	< .05
distractions	> 3	number of people	< 3	0.09	> .05	0.21	> .05	0.75	< .01

The process of combining two extremes of context, e.g. low activity and high distractions, achieves significant correlations and a new trend becomes apparent. Interestingly it is not the pleasure dimension that is seen correlating with PDI, it is the dominance dimension that is showing strong positive correlations with PDI under various combinations of disruptive contexts, shown in table 13.

These results are novel, with the author not having seen any previous reference to mobile device users relying upon their level of dominance to guide decision processes within a marketing context. These findings are of importance in that they provide guidance to the next cycle of research which focuses solely upon smart-phone device users. In the next cycle of experiments marketing advert simulations within everyday situations via a smart-phone application are implemented. Understanding this new phenomena presents an opportunity to develop novel hypotheses based upon the importance of user dominance and its relationship with decision involvement and, potentially, perception of different processing styles.

5.4   Cycle Three Results

5.4.1   User Perceptions of Advertisement Styles within Disruptive Contexts

This section presents the experimental results that focus upon the measurement of users' Message Perception when using the purpose-built Android application (SiDISense) while they go about their

everyday lives. The key aim of this experiment is to corroborate the hypothesis that disruptive contexts affect the relationship between user affective state and perception of different presentation styles, including *detail processing* and *mental imagery*. The belief is that the results will support the hypotheses for a layered model for context-aware recommender systems and for on-line advertising which will support the decision process that forms the style of engagement with the user. Previous cycles of experiments have already provided evidence to support the main research hypotheses. However, this experiment reiterates the surveys used but for a larger set of products and also uses a bespoke Android phone application to distribute the experiment's survey.

The use of the bespoke survey mobile application provides a number of benefits. Firstly the implementation of the survey is solely focused upon users of smart-phones accessing the process in a natural way i.e. via an application on their device. Secondly, the application controls how the survey is distributed to the participant. An automated process supported the need for participants to complete the survey multiple times on their personal device without too much additional effort to the participant. The application simply prompted the participant to complete the survey which they could either undertake or delay until the next opportunity. Finally, the application was also used to collect and process, in real-time, microphone and accelerometer data captured by the device. This as a process supported the development of the classification of disruptive contexts which were then purposed for the final context-aware system developed as part of this research.

Results have already shown that to determine user behaviour the PAD dimension of dominance-submissiveness could be as reliable, if not more reliable than the pleasure dimension previously relied upon. With this in mind it is therefore hypothesised that:

H11 – The Affective dimension of Dominance (dominance-submissiveness) will be a reliable scale within a mobile context to determine user perception of information processing styles (e.g. detail processing vs. mental imagery)

The experiment collects 310 usable individual results from 21 participants with 65% being male. The spread of age groups were as follows: 21 years and under (25%), 22 to 34 years (14%), 35 to 45 years

(32%), greater than 45 years (29%). Again two-tailed probability is tested for and where *p-values are statistically significant* they are shown as *p < .05* (confidence level of 95%) or *p < .01* (confidence level of 99%). The files showing the analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-v).

The result show that the detail processing style produces a significant positive correlation with level of dominance when tested for all collected data, albeit a relatively low one of $r = 0.23$, $p < .01$, whereas the pleasure and arousal dimensions produce virtually zero correlations (see table 14). As before the data is split into subsets of either high or low values for each disruptive context measured to determine their effect upon the perception and affective state relationships.

Table 14: Correlations for Detail Processing style

		Pleasure		Arousal		Dominance	
Context	Value	result	p-value	result	p-value	result	p-value
All data	-	0.006	> 0.05	0.018	> 0.05	0.231	< 0.01
Distractions	> 2	0.168	> 0.05	0.020	> 0.05	0.344	< 0.05
Noise	> 3	-0.244	> 0.05	0.533	> 0.05	-0.141	> 0.05
Activity	> 4	0.821	< 0.01	-0.522	> 0.05	0.772	< 0.01
Activity	<= 3	-0.055	> 0.05	0.107	> 0.05	0.231	< 0.01

The results presented in table 14 show that higher *levels of distractions* increase the amount of correlation between user dominance and perceptions of detail processing advert style. Note that both the dimensions of pleasure and arousal do not produce any correlation for distractions. A high level of *activity* also produces a similar effect with both the dimensions of pleasure and dominance producing significant increases in their respective correlations, $r = 0.82$, $p < .01$ and $r = 0.77$, $p < .01$. Note that both the dimensions of pleasure and arousal produce very few noteworthy correlations throughout. From this it is suggested that if a system was solely utilising a detail processing style then reliance upon the dimension of dominance as a measure of user affect when determining their perception of adverts.

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Table 15: Correlations for Mental Imagery style

Context	Value	Pleasure		Arousal		Dominance	
		result	p-value	result	p-value	result	p-value
All data	-	0.002	> 0.05	-0.082	> 0.05	0.096	> 0.05
Distractions	*> 3*	*0.741*	*< 0.05*	*-0.904*	*< 0.01*	*0.751*	*< 0.05*
Noise	*> 3*	*0.714*	*> 0.05*	*-0.714*	*> 0.05*	*0.775*	*< 0.05*
Activity	> 4	-0.844	< 0.01	0.097	> 0.05	-0.875	< 0.01
Activity	<= 3	0.241	< 0.01	-0.209	< 0.05	0.442	< 0.01

The use of mental imagery produces no correlation for any of the three PAD dimensions when looking at the full dataset. However, as level in contexts of noise, distractions, number of people or activity increase then so do correlations for all three of the PAD dimensions. As hypothesised an increase in the correlations assessed is found for level of distractions and level of noise and it is noted that they are very similar in their results (see table 15). As before within the results shown in section 5.3.2 the reader should note that the high activity data produces strong negative correlations for message perception using mental imagery adverts for both the pleasure dimension and dominance dimension. This is opposite to the results for perception of adverts using detail processing, which are positive correlations. This suggests that there is a clear indication as to which processing style is best suited when dominance or pleasure are high or low. This is an important finding in that it provides evidence for logic with discrete outputs representing preferred advert presentation style. This would be valuable to a mobile focused marketing campaign when determining a course of action when the level of user dominance and other contexts are known.

Overall the result indicates that the perception of information irrespective of an advertisement is affected by disruptions but depends on the level of activity. However, the forming of perception for detail processing advertisements does appear to be opposite to that of mental imagery. Again user dominance has been shown to be reliable, comparable with correlations achieved for the pleasure

dimension, especially for the detail processing style where far smaller and insignificant correlations in the other dimensions are produced. I can therefore reject the null hypothesis for *H11*.
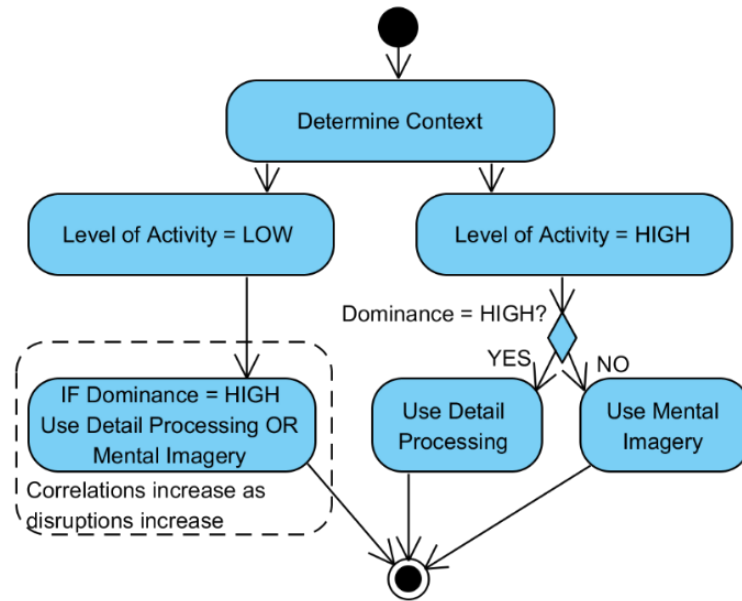
Figure 20: Representative model for determining appropriate presentation style

From the above results a set of rules are developed for use in a context-aware system that can apply different information presentation styles depending upon the user's affective state and other situational contexts. A model representation is shown in figure 20.

5.4.2 User Purchase-Decision Involvement within Disruptive Contexts

This section presents results of the Android application (SiDISense) experiment which investigates smart-phone users and their levels of purchase-decision involvement within differing situational contexts. I propose that the results will support the hypotheses for a context-aware m-commerce system which will be able to determine when best to engage with the user based upon their purchase-decision involvement. Previous cycles of experiments have already provided evidence to support the main hypotheses. This experiment will reiterate the survey process used but with a focus upon using a phone application for the task. As discussed in section 5.4.1 the use of the bespoke survey application provides a number of benefits including the collection of contextual data. Also the introduction of a

wider range of high involvement products will expand the scope of the experiment whilst corroborating the findings from the previous cycle of research.

The PAD dimension of dominance has been shown to be as reliable if not more reliable than the pleasure dimension, therefore it is now the aim to demonstrate that dominance will be the most important dimension when determining a user's purchase-decision involvement (PDI). It is therefore hypothesised that:

*H*12 – *The Affective dimension of Dominance (dominance-submissiveness) will be a reliable scale within a mobile context to determine a user's level of purchase-decision involvement*

From the twenty users participating in this experiment 277 usable individual results were gathered, with 60% of responses completed by female participants. The spread of age groups were as follows, 21 years and under (4%), 22 to 34 years (33%), 35 to 45 years (11%), greater than 45 years (52%). Again, for these hypotheses two-tail correlation is tested for, 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%). The files showing the analysis of data captured can be found on the CD attached to the appendix (see Appendix Q-vi).

For the full dataset produced no correlations are found between affective state and levels of PDI (pleasure r = 0.092, arousal r = -.019, dominance r = 0.092). As per previous results shown in section 5.3.2 in table 13, this suggests that there is no correlation between user affective state and PDI, however, where levels of different disruptive contexts become extreme in value, significant positive correlations are produced. Table 16 presents results for both high and low values for contexts of activity, noise and distraction and combinations thereof. Noise did not produce a significant correlation for any of the axes of affective state, whereas both high levels of activity and distractions did, therefore these two contexts are the focus of analysis.

Results show that all three PAD dimensions produce some evidence of positive correlations as these contexts increase in value, however, it is only a user's level of dominance that produced correlations

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with PDI with values large enough to be of significance. While still not an overly large correlation value it is shown that where distractions are greater than three out of five, an increase from dominance $r = 0.092$ to dominance $r = 0.38$, $p < .05$ is shown. Similar is also demonstrated for higher levels of activity (see table 16). These results are important because they demonstrate that mobile device users are subject to changes in environment when forming levels of PDI; this knowledge can then be used to inform a user engagement m-commerce model.

Table 16: Correlation between PAD and Purchase-Decision Involvement where high context values produce strong correlation for user dominance

		Pleasure		Arousal		Dominance	
Context	Value	Result	p-value	result	p-value	result	p-value
Noise	> 3	0.192	> 0.05	-0.023	> 0.05	0.269	> 0.05
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	> 3 > 2	0.220	> 0.05	0.270	> 0.05	0.440	< 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	<= 3 < 3	0.007	> 0.05	-0.007	> 0.05	0.092	> 0.05
Activity Distractions	<= 3 > 2	0.078	> 0.05	-0.056	> 0.05	-0.079	> 0.05

Again it is also the combination of high levels of disruptive contexts that produce the highest correlation; higher levels of *activity* and *distractions* produce a result of $r = 0.44$, $p < .05$. Again this is significant in that the increase from a zero correlation validates further the argument that increased levels of disruption will impact user cognitive capability, and that this is an important consideration for developing systems for the user of mobile devices.

The reader should note that in this new data, low levels of activity even when coupled with high or low disruptive contexts produce no correlation examples. Previous results for the extracted *mobile only* data (presented in section 5.3.2) demonstrated that high correlations were present where the level of activity was low and other disruptive contexts were high. This new data does however mirror the results in the experiment presented in section 5.4.1 – both detail processing and mental imagery presentations styles showed significant results when activity was high. It also reflects previous results shown in section 5.2.2. So, while the exact cause for this discrepancy is unclear it is probable that as this experiment's dataset is much larger, the results should be regarded as being more reliable. I should also reiterate that correlation is not causality and that there are probably many other aspects that are contributing to these results. These aspects will range from previously discussed contexts, including familiarity, to unexplored areas which could include personality types.

Table 17: Correlations between PAD and Purchase-Decision Involvement where user activity is high show that the correlation increases as Product Involvement decreases

			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 17 and table 18 further emphasise the importance of the dominance-submissiveness dimension by showing that as user Product Involvement decreases the correlation between the user's dominance and PDI increases in value. This is especially apparent when disruptive contexts are high. For example where Product Involvement is relatively low, i.e. less than 8 out of 15, the correlations increase dramatically, especially for the dimension of dominance which produces high correlations

when activity, ($r = 0.876$, $p < .01$), and distractions ($r = 0.931$, $p < .01$), have values of over three out of five.

Table 18: Correlations between PAD and Purchase-Decision Involvement where environment distractions are high show that the correlation increases as Product Involvement decreases

Context	Value	Product Involvement	Pleasure		Arousal		Dominance	
			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

This suggests that disruptive contexts have more of an effect upon user Purchase-Decision Involvement as their actual involvement with a product reduces, therefore, understanding a user's product involvement should also improve decision making results. However, whilst we would expect an e-commerce system, especially a recommender system, to have some knowledge of a user's level of Product Involvement for a specific product, this is not completely the case. Not only will a system not have insight into all products, the concept of Product Involvement, whilst a simple premise, is complex as it comprises of several layers (Houston & Rothschild, 1977). *Enduring involvement* is the level of a person's involvement that is always present – this could be static or may slowly change as taste, interests and other personally related contexts develop over time. *Situational involvement* is far more complex as its value will be reliant on the circumstances of how it is be consumed, therefore can be highly changeable and is dependent upon the user's situation (see Chapter two). Because of this, situational involvement will have more of a bearing, especially within the dynamic context of a mobile device user.

From this it is possible to state that knowledge of the user's Product Involvement may not always be available (complete or otherwise), however, online marketing techniques can model user behaviour that highlights user interest or likelihood of purchasing particular products, i.e. recommender systems, therefore this relationship is worth noting for future research.
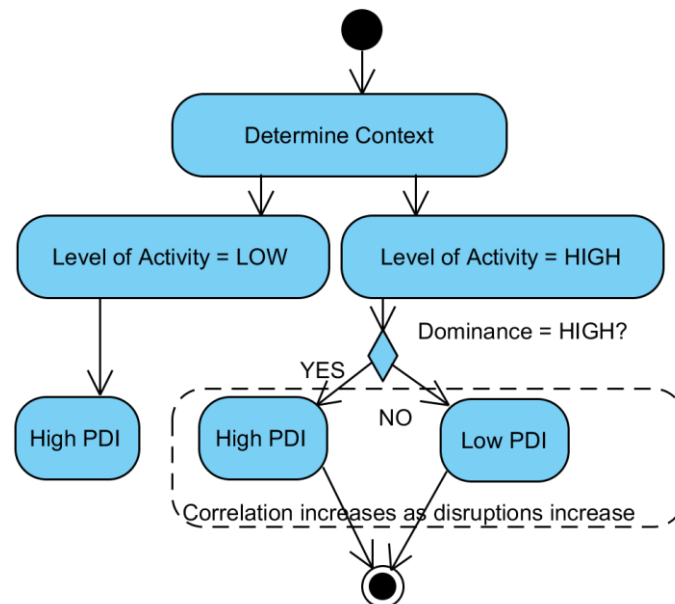
Figure 21: Representative model for determining level of user Purchase-Decision Involvement

The results suggest that user dominance is shown to be the most reliable axis of affective measurement, when using PAD, to determine the correlation with PDI when adverse values in stressor contexts are present, therefore I can reject the null hypothesis for *H12*. These findings enabled us to model a set of context based rules which can be used as logic to determine a user's level of purchase-decision involvement which can be implemented within a context-aware system, see figure 21 for a representative model of the logic.

5.5 Cycle Four Results

5.5.1 Success in Predicting Levels of User Product-decision Involvement and Perception of Advertisements

5.5.1.1 Initial analysis of data

This final SiDISense experiment's intention was to demonstrate a system that shows it is possible to determine when a mobile device user will have a high level of purchase-decision involvement and to also ascertain which presentation styles are most appropriate to engage the user through understanding of situational contexts. A total of 364 submissions from twenty-four participants were collected with 64% of responses completed by female participants. The spread of age groups were as follows, 21 years and under (6%), 22 to 34 years (22%), 35 to 45 years (14%), greater than 45 years (58%).

With evidence previously produced to support the main hypotheses it was important to validate these further using additional statistical analysis. This experiment uses the Two Sample T-Test to assess the logic developed for the implementation of context awareness and to provide further evidence to the research's key hypotheses:

H13a: That there is a statistically significant increase in average mean for user PDI when favouring the use of context-aware logic over non-context-aware logic.

H13b: That there is a statistically significant increase in average mean for user perception of advertisement styles when favouring the use of context-aware logic over non-context-aware logic.

The results of the Artificial Neural Network (ANN) classification system are initially discussed before addressing the above hypotheses. The success rate in classifying the *level of recent activity* was reasonable with 216 instances being correctly classified as either high or low, a 59.34% success rate. The classification of the *level of distractions* context produced better results with 282 instances being correctly classified as either high or low, a 77.48% success rate. In particular the classification of levels of activity suggest that a different approach may be needed, as the classification results of this experiment were lower than the findings seen when testing the previously collected training data (see section 4.4.3). It is probable that either a larger data set is needed or that behaviour is more specific to the individual and that a system requires an element of learning on each device.

To produce results that could prove the above hypotheses the system was required to produce data for both context-aware and non-context-aware use. This was achieved by simply alternating between

utilising *context-aware logic* and *non-context-aware* logic when implementing the survey. The context-aware logic determines which presentation style (detail processing vs. mental imagery) should be selected before then determining whether to advertise; the non-context-aware logic follows an 'always advertise' and an 'always use the detail processing presentation style' implementation.

The above process produced three specific sets of data, however the experiment would have benefited from a fourth set of data being captured when further analysis was undertaken. Ideally the context-aware logic should also have always advertised whilst identifying the instance with a 'would not have advertised' flag where appropriate. This would have provided an additional comparison between advertised instances and non-advertised instances for analysing the perception of presentation style decision logic and not just an advertised vs. random instances comparison. The method above produced the following sections of data:

1. *context-aware-advertised* – context-aware logic decision to advertise using either mental imagery or detail processing
2. *context-aware-not-advertised* – context-aware logic decision to NOT advertise but captures the response which would have been to compare with context-aware-advertised
3. *non-context-aware-advertised* – always advertising using detail processing for comparison with context-aware-advertised

Each of the three elements in the purchase-decision involvement tool is measured by the user from one to five, these are then added together to produce a result along a scale from three to fifteen. All the user responses within each of the three datasets above are then averaged so that the Two Sample T-Test can be applied. The average purchase-decision involvement mean for each of the three datasets above is as follows, 11.6, 11.04, and 11.49 respectively. Note that datasets one and two utilise only data that has 100% accuracy for classification of both *level of activity* and *level of distractions,* i.e. the classification fails were removed from these datasets. From the results it is seen that there are no significant results when comparing the dataset (see in Appendix Q-vii). The results for the *perception*

of presentation styles section of the experiment also failed to provide any significant results that would support the rejection of the null hypothesis developed.

In an attempt to extract positive and significant results from the data captured in this experiment the data has the classification results removed. In doing so the full dataset becomes available to aid further analysis into why the results discussed above were not as expected. Initially the original context-aware logic is applied to the dataset using Microsoft's Excel software. This process produced the following datasets, 1) context-aware-advertised and 2) context-aware-not-advertised, (see implementation in Appendix Q-viii). Note that there is already a third dataset *non-context-aware-advertised* which represents a static system that always advertises using detail processing.

With a slightly larger dataset available and using the original SiDISense logic the purchase-decision involvement average means for *context-aware-advertised* and *context-aware-not-advertised* were 11.89 and 11.3 respectively. Note that the average mean for *non-context-aware-advertised* remains at 11.49. A comparison is made between using context-awareness logic to determine whether to advertise and the notion of always advertising using detail processing i.e. non-context-aware-advertised, and a small, non-significant, increase of 3.45% is seen. The average mean for both *context-aware-advertised* and *context-aware-not-advertised* are also compared which produce another small increase where advertising, 4.94%.

The results above suggest that there is a fault in the hypotheses or errors in the logic used to implement the context-awareness part of the system. In the following section a further analysis upon the context-aware logic used to demonstrate that the method devised is of benefit to m-commerce is presented.

5.5.1.2 Further analysis - Modifications to logic

Following additional analysis it was noted that by using the original logic structure developed but with adjustment of some parameters a significant increase is seen in the performance when analysing purchase-decision involvement. See the revised logic in figure 22. The values for *context-aware-*

advertised and *context-aware-not-advertised* and *non-context-aware-advertised* being 12.79, 11.5 and 11.48 respectively; for implementation of the modified logic see Appendix Q-ix.

Comparing the average mean for *context-aware-advertised* and *non-context-aware-advertised* Again the two sample t-test is used and a significant increase is found where the context-aware system was applied of 11.39%, $d = 1.3, p < .05$. Making the comparison between *context-aware-advertised* and *context-aware-not-advertised* there is a significant increase of 11.18%, $d = 1.29, p < .05$, in the average mean in favour of where adverts are placed. These minor changes in logic parameters validate the hypothesis developed and therefore I reject the null hypothesis for *H13a*. While the percentages were relatively 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.

Unfortunately the above method could not be applied when attempting to prove the validity of the perception of presentation styles section of the experiment. This was due to failing to capture the data for the "do-not-advertise" instance responses as mentioned previously. Without the additional dataset a full comparison could not be undertaken using the Microsoft Excel implemented context-aware logic due to all the instances captured being results of non-disruptive scenarios.

In an attempt to validate the use of the context-aware logic for determining appropriate presentation styles I analysed the data from a previous experiment as detailed in section 4.4.1. This experiment followed the same survey implementation and used an identical product list and product details for both detail processing and mental imagery presentation styles. I found that applying a single revised logic parameter (see the revised logic in figure 22) to this dataset produces significant results when assessing the perception of presentation styles as measured using *eab_perception*. The following steps were used to produce a usable dataset (for implementation see Appendix Q-x):

1. Apply the New logic to the Excel sheet
2. Remove instances where the SiDISense logic derived presentation style and the presentation style used in the experiment (4.4.1) are not identical
3. Separate the data into two sheets 1) Advertise and, 2) Not Advertised

```java
boolean usingDetailProcessing = true;
boolean advertise = true;
int userCase = 0;
// Step 1
if (activity >= 3) {
   if (user_dominance >    P1
      userCase = 1;          // use detail processing
   } else {
      userCase = 2;     // use mental imagery
      usingDetailProcessing = false;
   }
} else { // low activity
   if (user_dominance > 3) {    P2
      userCase = 3;     // using detail processing
   } else {
      userCase = 4;     // Neither processing type work
   }
}
// Step 2
if (userCase == 1 || userCase == 2) {
   if (distractions <= 3) {    P3
      userCase = 5;          // PDI is higher so advertise
   } else {
      advertise = false;   // PDI is lower so do not advertise
      userCase = 6;
   }
} else if (userCase == 3) {
   if (distractions > 3) {    P4
      userCase = 7;        // Perceptions higher so advertise
   } else {
      advertise = false;  // Perceptions are lower so do not
advertise
      userCase = 8;
   }
} else if (userCase == 4) {
   advertise = false;     // Perceptions are lower so do not
advertise
}
```

	Original logic	**New logic PDI**	**New logic EAB**
Parameter - P1	*user_dominance > 3*	user_dominance > 4	No change
Parameter - P2	*user_dominance > 3*	user_dominance > 4	No change
Parameter - P3	*distractions <= 3*	distractions < 2	No change
Parameter - P4	*distractions > 3*	distractions > 2	distractions > 2

Figure 22: SiDISense context-aware logic with revisions table

A total of 85 instances were extracted using the new logic to produce a new dataset where the product would have been advertised using either detail processing or mental imagery. The average mean results for the *context-aware-advertised* data improved upon the *non-context-aware-advertised* EAB data by a significant increase of 7.74%, $d = .8$, $p < .05$. A total of 144 instances were extracted using the new logic to represent *context-aware-not-advertised* data. Comparing this data to the *context-*

aware-advertise dataset produced a significant increase of 14.14%, $d = 1.1$, $p < .05$ in favour of placing the context-aware adverts. Therefore from these results I can reject the null hypothesis for *H13b*.

5.5.1.3 Summary

The complexity of the data processing in this final experiment led to a number of issues. Firstly, the limited success achieved by the context classification routine led to a reduced dataset size to which the system logic for determining the appropriate level of interaction could be applied and thus produced insignificant results. I was able to address this by instead using the contextual values provided by the participants when they completed the survey; this provided a larger dataset on which to test the hypotheses. Secondly, an adjustment of the parameters of the context-aware logic was required to produce significant results for both parts of this experiment. I also acknowledge that the participants involved were loaded towards the older age group. This may also have skewed results, however as the overall findings matched that of previous cycle's results I am confident that consistency is achieved.

To validate the hypotheses two mean comparisons are made using the statistical two sample t-test, the first between the *context-aware-advertised* and *non-context-aware-advertised* system options, and the second a comparison between *context-aware-advertised* and *context-aware-not-advertised.* The results of both demonstrated that using context-awareness produced a higher average of success in both assessment of purchase-decision involvement and advertisement perception. Together the results help determine that m-commerce and user engagement can be improved using context awareness that focuses upon physical contexts and cognitive processes. While the percentage increases are relatively low they could have substantial impact when considering the volume of e-commerce product placements and the cost involved for advertising.

5.6   Chapter Summary

This chapter has presented the results for a total of seven experiments that have primarily focused upon two main areas of user cognitive behaviour i.e. perception and involvement. Each experiment has elaborated upon aspects of these areas with hypotheses becoming refined with each set of new findings. The key research aims have however remained unchanged where the work presented in this chapter has sought to demonstrate that user and environmental contexts will affect cognitive behaviour which could be used in mobile commerce systems that seek to maximise engagement potential.

The initial focus of this research was to identify relationships between cognitive processes such as forming of perceptions and making decisions. The results of the experiments identify that certain relationships between affective state and cognitive processes differ depending on the computing device in use. Whilst previous research has suggested that user pleasure and cognitive processes are related, evidence is provided that when using mobile devices, in particular smart-phones, a user relies more upon their emotional state when forming perceptions of textual messages and simple advertisements of various forms of cognitive processing e.g. detail processing and mental imagery. Also identified is that other aspects of affective state are important when assessing engagement of mobile device users. For user perception of different processing styles, both pleasure and dominance seem to be equally relied upon, however when forming levels of purchase-decision involvement the dominance dimension is particularly important, if not solely relied upon, in the user's cognitive processes.

In addition to furthering insight into aspects of relationships between a user's affective state and cognitive abilities the findings demonstrate how physical contexts influence these relationships. Disruptive contexts including levels of noise, distractions, number of people and familiarity, strengthen existing cognitive relationships. For example where levels of distraction were high and the user's level of dominance was also high then the user's perception of advertisement content and

purchase-decision involvement would be higher than if the level of dominance was low. For instances involving familiarity it would be the lower values i.e. unfamiliarity that produced this effect.

Level of activity was found to be critical for mobile device users forming purchase-decision involvement. Where the level of activity was high, any results achieved from other disruptive contexts would be strengthened. However where level of activity was low, higher distractions, for example, would produce less of an effect and results would be relatively uniform along the pleasure-displeasure and dominance-submissiveness dimensions. Activity also produced a very different result when developing perceptions of adverts using mental imagery than it did for detail processing ones. When activity was high the correlation produced between dominance and perception of detail processing was strong and positive, the opposite however was true for mental imagery adverts which were strong yet negative. In addition to this for high activity instances involving mental imagery it was found that other contexts had minimal effect. Finally where activity was low, both processing styles produced positive but lower correlations with the dimensions of affective state.

The above findings supported the development of context-aware logic for a bespoke system in the last experiment. The system not only used an ANN to classify physical contexts (see section 4.4.3 and section 5.5.1.1), but also the logic developed determined which method of advertisement style was to be used and also whether to actually advertise or not. While the classification of user activity achieved a success rate of only 59% the classification of the level of distractions fared better with 77% success. Both of these results were lower than in the previous testing of the classification routine which suggests that either the training dataset needs to be larger or the approach needs further work.

While the classification did not produce the results required it was still possible to test the final hypotheses. It was found that using context-awareness benefits a system based upon purchase-decision involvement and user perception as guides to user engagement with mobile product placements. The context-aware logic, while needing some adjustments, produced significant results that supported the use of context-awareness for determining whether to advertise or not and the use of suitable advertising styles. In addition to the above the reader should recall that the results are based

upon a system that utilises only activity and distractions as the contextual disruptions affecting behavioural relationships. Adopting additional disruptive contexts as identified in previous chapters, i.e. interaction and familiarity of people and location etc., will ensure enhanced insight and improve results.

The following chapter will discuss and reflect upon the key research questions and will then discuss in detail the meaning of the finding presented above. This discussion will include an assessment of similar research works which will compare and contrast findings in order to demonstrate why the findings are important. Limitations in this research and any issues that arose from these limitations will also be discussed.

6. Discussion

6.1   Introduction

This research has focused on context-awareness and determining user cognitive behaviours which can be used to show indicators of potential user engagement with e-commerce systems whilst using mobile smart devices. This is a relatively unexplored area of m-commerce recommender systems and on-line product placement. The research demonstrates that while a user can be favourable towards purchasing a product, i.e. they have a high level of involvement in the product purchase decision process, if their situation means that they are unable to process the product information, for whatever reason, the product placement will not be successful. The key question was whether by identifying a user's level of engagement it is then possible to enable a recommender system to determine whether to place a particular product and identify the best style of advert which would suit the user's current cognitive capacity?

The research's main objective was to implement a context-aware system that utilized both user and environmental contexts to demonstrate effects upon user-product engagement which could then be used as a preliminary phase to a marketing or recommender system process, i.e. whether to make the product placement and then adopting the best method for engagement.

This research follows three key questions:

I.   Can a context-aware system using both user and environment contexts be able to determine what style of product placement is suitable for a high involvement product or service?

II.   Can a context-aware system using both user and environment contexts be able to determine when to make a product placement for a high involvement product or service?

III.   Will a context-aware system using both user and environment contexts achieve higher levels of user engagement than a non-context-aware system if armed with the capabilities of hypotheses in I & II?

A total of seven surveys were completed as part of the research effort, these involved self-administered questionnaires that ranged from paper-based to a bespoke Android smart-phone application. The distribution of the surveys was mostly conducted electronically either via email, social media or the University's own teaching and learning platform.

The sample size varied between surveys, however the results were typically large enough to ensure statistically significant results. Each survey followed a relatively consistent format and included self-administered questionnaires for measuring *purchase-decision involvement* (Mittal, 1989), *user perception* utilising the semantic differentials method and three dimensional emotion theory in the form of *pleasure-arousal-dominance* emotional state model (Mehrabian, 1996).

In addition to the implementation of these tools the novel *disruptive contexts questionnaire* was developed. This questionnaire was used to collect user data based upon subjective impression of user environment and activity. This focused upon the contextual areas of noise, distractions, familiarity with people and places, number of people in the vicinity and the level of user activity. These physical contexts were labelled as disruptive as it was hypothesised that cognitive processes would be affected by extremes in these contexts and that this would then impact the completion of a task such as digesting information. Together these supported the development of system logic which could utilise context-awareness to determine when and how a recommendation would be presented to a user to maximise their engagement.

The purpose of this chapter is to provide an in-depth evaluation of the research completed. The discussion will focus on providing insights into the results produced using comparisons with previous research findings and observations of current practices within the industry sector to gauge the impact of the research outputs achieved.

The following sections initially summarise this research's findings before discussing in detail the implication of the results and their effect upon different areas within e-commerce. The main focus is upon the importance of user dominance within the mobile device user's decision processes and also the influence that disruptive contexts have upon these relationships. Also discussed are the

possibilities of implementation of the context-aware model developed within the use of recommender systems and also how the classification of levels of disruptive contexts can be taken forward. Before concluding, this chapter also reviews the methodology followed providing mindful comments to any limitations in the approach conducted in this research.

6.2   Summary of Findings

This project aimed to show that knowledge of user cognitive capabilities, e.g. perception of different information presentation styles and level of purchase-decision involvement, can act as an additional layer to the traditional recommender system model by determining the method of engagement with a user. In addition to the primary objective of a recommender system of determining 'what' to advertise or recommend, it is now proposed that establishing the 'when and how' in implementing a specific product placement will increase the effective user engagement, be it purchasing or brand awareness, in an m-commerce context.

To explore the notion that a system can determine when and how to place a product advertisement a number of existing tools and methods were selected to conduct the experimentation. Purchase-decision Involvement differs from Product Involvement and was specifically developed to measure a consumer's mind-set rather than a behaviour manifested in the decision making process (Mittal, 1989). It has been ascertained that high values in purchase-decision involvement should result in the system choosing to engage with the consumer. Similarly to address how a system can determine what style of advertisement would be more conducive to a consumer's engagement, a short scale of semantic differentials was used to gauge the level of user perception of the content of the advert. This scale was used to assess both simple text and adverts of different styles. Initially the research used several opposing styles of presenting information, namely detail processing, mental imagery, high or low effort, high or low risk, fear appeal and optimistic appeal. The research effort later focused upon detail processing and mental imagery styles as these (in particular detail processing) seemed to be the most widely used in current e-commerce.

Previous research had already shown that user affective state (mood, emotions etc.) can influence purchasing behaviours, e.g. (Otero-López & Villardefrancos Pol, 2013), (Adelaar, Chang, Lancendorfer, Lee, & Morimoto, 2003), (Consoli, 2009). Therefore it was ascertained that the context of user affective state was essential to the research undertaken herein and to demonstrate the level of user affective state the research implements a graphical representation of the three dimensional emotion theory *pleasure-arousal-dominance* (Mehrabian, 1996). For an in depth discussion on this approach, see Chapter two.

The implementation of the above proved to be essential to the research conducted and provided a sound foundation from which to develop the hypothesis outlined in the previous section. Utilising existing theories supported the development of the novel disruptive contexts model through which it was possible to demonstrate that disruptions impacted upon cognitive preferences which could then be used to inform e-commerce systems of likelihood of a device user's engagement.

The following briefly outlines the research findings:

I.   That a context-aware system can be used for determining levels of cognitive capacity which can then be used as an indication of user engagement with e-commerce product placements.

II. Relationships between affective state and some cognitive processes will differ depending on the type of computing device in use. The context-aware system particularly lends itself to use with mobile devices.

III. Knowledge of relationships between affective state and cognitive processes, such as forming of perceptions of information presented via a mobile device and the user's ability to form a high level of purchase-decision involvement, can be modelled to support the development of a novel context-aware system.

IV. From the use of Mehrabian's (1996) three dimensional model of emotion I show that the often ignored dimension of user dominance appears to be equally if not more important than the other scales of the model. In the formation of purchase-decision involvement and perception, user dominance proves to be the most resilient for modelling users of mobile devices.

V.   That e-commerce systems require a physically orientated context-aware approach when engaging with users of mobile devices. Both physical behaviour and environmental contexts demonstrate influence upon cognitive capability in forming levels of purchase-decision involvement and perception when using a mobile device.

VI.   The user's level of activity is critical to mobile device users when forming purchase-decision involvement and levels of perception of product information. Physical activity appears to be significant in determining these behaviours, with high activity and high dominance being fundamental in indicating strong levels of cognitive capability.

VII.   Disruptive contexts including levels of noise, distractions, number of people and familiarity, impact upon existing cognitive relationships. The contexts act as stressors to relationships between affective state and cognitive processes with particularly negative effect upon mobile device users with low dominance.

6.3   The Measurement of Affect and the Case for User Dominance

User Affective State (i.e. mood and emotions) was identified as key to understanding user engagement and this research utilised Mehrabian's (Mehrabian, 1996) three dimensional model of Pleasure, Arousal, Dominance as a concatenated reading for all of a user's affective phenomena. It is important to remember that many findings focusing on affective-cognitive relationships have demonstrated the usefulness in understanding levels of pleasure in emotions and mood. However these have been primarily achieved through the use of experiments within controlled environments and not necessarily even using computing devices, e.g. (Parboteeah, 2005), (Hansen, 2005), (Bloch, Sherrell, & Ridgway, 2014), (Myers & Sar, 2015) to name but a few. While the role of pleasure and arousal is well established within retail settings (Yani-de-Soriano & Foxall, 2006), the research was focused upon demonstrating that for users of smaller mobile devices within dynamic environments, different aspects of our affective state are as, if not more, important.

It is clear from this and other research results that cognitive phenomena, e.g. the forming of purchase-decision involvement and consumer perception 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 (Calvo & D'Mello, 2010). In particular a user's level of pleasure has been shown to be key to findings related to on-line marketing (Parboteeah, 2005), the browsing for information, and the purchasing of products (Bloch et al., 2014). The results however have identified that user dominance can also be an important factor in mobile device users' cognitive processes. This finding aligns itself with other research statements that dominance is as legitimate as pleasure and arousal dimensions and should not be ignored when considering consumer behaviour and retail marketing (Yani-de-Soriano & Foxall, 2006). Broekens, (2012) 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 dimension 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 (Lerner, 2000). Online shoppers could also be relying upon dominance to maintain control of their shopping situation by choosing online rather than traditional retail outlets (Eroglu et al., 2001) and with high control (dominance) are more likely to respond to sales or bargains (Youn & Faber, 2000).

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 (Danciu, 2014) or the use of 'priming' which presents the device user with different stimuli which are intended to influence the response to a latter stimulus i.e. the final advert, (Kramer, Guillory, & Hancock, 2014). While advertising techniques are tried and tested within traditional and online marketing these tend to focus upon levels of positivity (pleasure) and arousal (Bagozzi, Gopinath, & Nyer, 1999), (Martin, 2003), (J. Park et al., 2005), (Myers & Sar, 2015). The inclusion, if not the sole focus upon user dominance could be a benefit to the advertisement process on 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 evidence in demonstrating the importance of user dominance in an m-commerce setting is a key research contribution achieved in this work.

This concept could also be of benefit 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 has 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, and this film would also be recommended to other viewers looking for the same level of enjoyment (Bennett & Lanning, 2007). This process is based upon methods of simple human observation where we determine suitable items through previous behaviour (Schafer, Frankowski, Herlocker, & Sen, 2007). 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 (Winoto & Tang, 2010). This suggests that predetermined mood or emotions can influence the method of system-user engagement and aligns with the hypotheses and research findings in determining how to engage with a user.

Utilising emotions and mood within a CARS consumption phase is relatively straightforward to implement as it will primarily rely upon user feedback as the determining factor. For a system to utilise elements of user affective state, i.e. dominance, as an input context for determining a 'recommendation', the device that the user is using would be required to measure their behaviour and ascertain their level of dominance. Amongst others, Likamwa, (2012), recognises the potential benefit of using mood as an input into a recommender system, however I am not currently aware of any research efforts that have attempted to determine a relationship between the mood and the user's cognitive capacity before making a recommendation. While there are many research examples that demonstrate attempts to measure levels of mood or emotions this is not a simple task and results are not particularly reliable and do not provide definite insight into consumer dominance.

There are several methods for executing the measurement of mood and emotions or indeed affective state. Dimensional theory was selected over an Appraisal theory due to their requirement of a fully described situational representation with specifications that force assumptions on system representation (Gratch et al., 2009). In other words Appraisal theories require a great number of 'appraisals' measurements (Marsella et al., 2010), which while appearing to suit the need for contextual detail to establish consumer behaviour, is too complex when compared to the smaller number of measurements that are used by dimensional theories. As a method for use alongside additional survey questionnaires the dimensional theory suited the requirement for a swift, concise and repeatable representation of affective state.

Throughout this research effort I have utilised Mehrabian's (Mehrabian, 1996) Pleasure-displeasure, Arousal-nonarousal, Dominance-submissiveness (PAD) dimensional model in the form of the psychological tool called the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994). The use of the PAD-SAM combination has provided an inexpensive way of implementation for capturing user affective state. Whether implementing in paper or electronic form the method has proved to be consistent in terms of criteria of use acceptance and collection of data. As with all Likert scale based data collection there is always a tendency towards central tendency bias, however in the experiments there is a reasonable spread of data across all three dimensions of PAD. Using this method has allowed us to capture an accurate yet subjective interpretation of the user's affective state. While it is possible that some users may interpret some feelings incorrectly most have a good level of emotional intelligence which can be embedded within a recommender system (González et al., 2007). Following these standardised processes of using subjectivity to measure the holistic measure of affective state provided a stable platform from which to gauge the effect of the main areas under investigation i.e. situational context and cognitive behaviours.

To have attempted to measure the participant's emotion or mood automatically in this project would have introduced another layer of complexity, however for the concept of a context-aware / cognitive-aware system becoming fully realised in a commercial sense, an accurate method for measuring a three dimensional representation of affective state would have to be implemented. Thus far few

attempts have been made to do this – methods have tended to focus upon measuring specific moods or emotions rather than semantic differential scales, i.e. dominance - submissiveness.

While many examples demonstrate measurement of mood and emotion it is important to first recognise that the mobile devices are unique in their size and typical use, though as these devices become ever more computationally powerful this seems to be changing. Calvo & D'Mello, (2010), explore a wide range of perspectives and processes used in Affective Computing and summarise that modalities including facial expressions, voice, body language, physiology, brain imaging etc. can all be used to conceptualise emotions though not all are viable for a mobile platform. While these methods require significant levels of processing power with careful optimisation they can be implemented on a mobile device (Miluzzo et al., 2008). There are also many programming libraries within this area that are available to the developer.

Some methods are going to be more useful than others. Using facial expression recognition has a potential as the user will tend to be facing the device whilst using it, though levels of movement and variance in the device angle may make consistent recognition accuracy problematic. Also, depending on the user, one of the device's cameras may not always be facing the user's face, for example, the traditional taking of a call by placing the phone against the ear would be completely ineffective in capturing the required facial details. Using data from typical smart-phone applications, e.g. SMS, email and phone calls, a system can utilise statistical usage models and learn to estimate mood through the analysis of behavioural patterns of phone use and the content of communication (Likamwa et al., 2011), (Ma et al., 2012). However these will be less effective in identifying sudden emotional changes. On-line social networks, including Twitter, Facebook and MySpace, have also been used to support the understanding of user moods, however these are mainly text based systems, for an example see Nguyen's et al.'s work (Nguyen, Phung, Adams, & Venkatesh, 2014). MoodMiner (Ma et al., 2012) also uses communication data, e.g. call logs and texts, to support extraction of behaviour pattern and provide assessment of daily mood. However, as mood has a strong time correlation and changes little day-to-day the approach needs to be more considerate to the presence of emotions to be able to provide an accurate measure of affective state.

As well as the camera and phone applications the smart-phone typically comes with several electronic sensors. These have often been used effectively to capture situational contexts and in some cases successfully categorised aspects of mood and emotions (Ma et al., 2012). The phone's microphone is the most recognisable of these and in particular is an important tool for classifying not only speech as generated by taking a call or background discussions but also non-linguistic vocalisations e.g. a laugh or yawn. Through these vocalisations we show displays of stress, boredom and excitement. However classification of affective states tends to be more accurate using facial expressions (Calvo & D'Mello, 2010). Also, whilst it is possible to categorise a yawn, for example, it is more of a challenge to then determine whether the yawn was released due to tiredness, boredom or even nervousness. The use of discrete labels complicates matters whereas these three labels could all suggest a low level of user dominance which simplifies the outcome somewhat.

Another useful sensor is the accelerometer which has been used to identify activities such as walking or jogging for example, (Kwapisz et al., 2011). This could provide insight to a user's mood as could understanding levels of user micromotion, (Ma et al., 2012), which is the regular patterns of movement of the phone, i.e. the regular picking up of the phone for very short periods could indicate nervousness for example. Olsen & Torresen, (2016) suggest that emotions can be measured through the use of the accelerometer whilst placed in the pocket. They measure emotions using the two dimensioned Circumplex model (James A Russell, 1980) which suggests that this is really a concatenation of all emotions that we are subject to at a particular point in time. They do have some success and while they do not address dominance as part of their experiment it seems possible that this method may provide some insight to a mobile user's affective state.

It becomes apparent that while the above demonstrates that user behaviour can provide insight to aspects of affective state, none of the methods thus far can provide a truly accurate and reliable solution. It is entirely probable that multiple methods will need to be utilised to produce an outcome. Achieving this will be critical to a commercial system that follows this research or indeed any system that relies upon measuring affective state. This research's identification of user dominance as being

key to modelling mobile device user behaviour demonstrates the importance of achieving this goal, and is a major contribution of this work.

6.4   Disruptive Contexts and their Effect

Through the practice of exploring a person's positive emotions, previous results have shown that it is possible to determine levels of cognitive phenomena of both consumer purchase-decision involvement (Hansen, 2005), and perception of advertisements (Myers & Sar, 2015). However from the findings this method seems only consistent when considering relatively static environments and larger computing devices. Where small mobile devices are being used in environmentally diverse situations it was initially thought that this relationship is not apparent in any of the pleasure, arousal, dominance dimensions, in fact no relationships initially appear present. This could be due to the wider range and combination of contexts involved which therefore confuse any underlying patterns.

What the findings demonstrate is that extremes of contexts associated with the user environment and user behaviour appear to form relationships between the cognitive processes, e.g. purchase-decision involvement and perception, and the user's affective state. This appears logical in that, not only is cognition a complex process involving many domains, including emotion, memory and attention, but a mobile device user's environment can be far more diverse than that of someone using a static device. Dynamic contexts that the mobile user is subject to are also potentially exposed to uncontrollable levels of disruption and when compared to a desktop computer user these extremes could have an effect on capability in completing tasks.

So with mobile device users being potentially subject to extremes in environment disruptions, I have focused upon several contexts that have been previously shown to be disruptive, i.e. noise (Guski et al., 1999), distractions (McGehee, 2014), activity (Hogan et al., 2013), and unfamiliarity of places and people (Paulos & Goodman, 2004). This research, together with the findings herein, supports the novel concept of *disruptive contexts*. Disruptive effects are more of an issue for the mobile user when compared to the static user, who is not exposed to such a variety of potential environmental contexts and generally completes tasks within a familiar place. Mobile users are also subject to changes in their

own mobility, i.e. the type of activity and purpose of that activity. In other words we may write an email at home or in a shopping mall for example. This notion perhaps explains further why some results presented no immediate patterns in relationships and required extremes in disruptive contexts to take effect before becoming apparent.

One of the main focusses of this research has been to show how these contextual disruptions impact upon cognitive processes, i.e. the forming of purchase-decision involvement in a mobile context. The results, as previously presented in Chapter five sections 5.3.2 and 5.4.2, 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., (2012), 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 and purchase intent are not possible for users experiencing weak emotions and aligns itself with this research's findings that low dominance in mobile users leads to low levels of purchase-decision involvement.

I have presented similar results in the form of a relationship between affective state and user perception of information presented via a mobile device. In some cases results show that high levels of activity cannot only strengthen the relationship but also reverse the relationship where perceptions are measured for different types of advertisement presentation styles. This suggests that with knowledge of certain contexts it is possible to ascertain suitable presentation styles which will support different advertising objectives, i.e. whether to attempt enticing someone to make a purchase or to provide information for product or brand awareness only. Demonstrating the importance of disruptive contexts in the cognition process presents several benefits within decision reliant systems, including recommender systems. The relationship patterns discussed above enabled the development of a key

research contribution by demonstrating that a context-aware system process will achieve a higher positive engagement with consumers than a simpler non-context-aware process.

While the final results in comparing the mean difference between context-awareness and non-context-awareness were significant, the results were not particularly high (ranging between 7.74% and 11.39%), however these are still of potential benefit to improving advertisement campaigns or recommender system effectiveness. Even though a mobile user's situational context is diverse, the results are testament to the fact that even modelling a low number of disruptive context is enough to capture the effect sought. The reader should remember that the final experiment only utilised two disruptive contexts, activity and distractions. The inclusion of additional disruptive contexts will no doubt increase the performance of the context-aware process designed, as would any context that provided insight into the consumer-product and the consumer-environment relationships.

6.5   Further Insight into Disruptive Contexts

The use of the term *disruptive contexts* is to suggest that these contexts are altering our cognitive function. In this section the complexity in the categorisation of disruptions is discussed further. In this research disruptions have have identified as primarily being noise, distractions, familiarity and activity, however the depth of the investigation into their effect on cognitive behaviour has been limited to demonstrating results that suit our immediate needs. The findings herein indicate that the model developed has scope for improvement, therefore further discussion on the complexities behind 'labelling' contexts and the concept of developing a model that is complete is required.

From the results it is seen that noise has a disruptive effect when at very high levels, in particular when associated with other disruptive contexts with high levels. The label of 'noise' obviously overlaps with the use of the label 'distractions' so is therefore a very simple method of ascertaining a level of distraction. This however would not provide a realistic model. 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. (2012) 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, it is possible to 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. The above suggests noise cannot be considered of its own accord but together with other contexts which develop the overall effect of the sound by understanding other environmental contexts, e.g. distraction, or by understanding the person's behavioural traits. Both provide their own complexities, however it is logical to develop an environmental model from which a behavioural model could learn from the effects of multiple contexts.

The context label of distractions is yet more complex and is itself essentially multi-contextual. While this project's use of the microphone as a measurement tool for capturing the audio aspect of distractions appears singular in its approach, the information it would have captured 'contains' complementary information. For example visual distractions are related to but not solely linked to audio distractions. Therefore there would have been occasions when the measurement of the audio distraction would have captured the participant's additional involvement with a visual distraction. The notion that non-audio distractions, e.g. visual, can be associated with an audio distraction provides an indication as to why the measurement and classification of the user's interpretation of distraction was successful. Essentially we are witnessing the fact that some distractions are being measured through their association with noise. This may suggest that either an audio distraction has more impact than a non-audio distraction, are more prevalent, or that most non-audio distractions are accompanied by noise. Either way it appears probable that capturing non-audio types of distracting contexts should be considered as an additional part of the disruptive model to increase further the classification accuracy of user's subjective notion of distractions overall.

Distractions can also be present in the form of physical pain and can impact upon someone's ability to focus or complete tasks (Moriarty, McGuire, & Finn, 2011). Distractions such as music are used however in the treatment of pain (Eccleston, 1995), therefore while being a potential distraction, music could also be the facilitator in a user being able to focus on a task. So while distraction can manifest itself in many ways, including audio, visual and physically, it can also be task related. 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.

The notions of distractions can also be dependent on the task being attempted. Someone absorbing some important, detailed information may be easier to distract when compared to another playing a game. However this phenomena may be entirely dependent upon the individual and their ability to 'zone out' and focus on the task at hand. 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 (Anderson, Bierman, Franko, & Zelko, 2012). While additional distractions and their potential effect on cognitive behaviour have been discussed, the nature of the research herein should also be recognised. The Android system developed is obviously a distraction in itself when it requests the participant for a response. The fact that the participants were already using the device before the system request confirms that some level of distraction can be managed depending on the task.

Another element of disruption explored in this research is familiarity of the environment and the people therein. While the contexts were not the focus of the final experimentation, the initial results demonstrated a positive indication that they fit within the novel concept of disruptive context, especially when considered with other disruptive contexts, and support my call for further research into their value. Previous efforts into understanding familiarity within a recommender system context have focused primarily upon the familiarity the user has with the recommended item (Sinha & Swearingen, 2002) or the familiarity between users when online and using the same platform i.e. where two or more users of a social network have certain levels of familiarity with each other (Jeckmans, Peter, & Hartel, 2013). This use of familiarity demonstrates that it is important in improving the effectiveness of the recommender system. It is therefore reasonable to suggest that by including familiarity that the user may have with their situation could enhance the effectiveness of these methods. This as a hypothesis links primarily to the notion of online trust and transparency. If

familiarity is linked to, say, trust online (Komiak & Benbasat, 2006) and also to when forming opinions or feelings based upon immediate physical environment (Sundstrom & Sundstrom, 1986), then it is prudent to assume that the representation of both phenomena would lead to a more effective solution to modelling behaviour.

The results have indicated that low levels of aspects of familiarity affects our ability to form high levels of purchase-decision involvement. This supports the theories that familiarity is a cognitive variable that facilitates task performance (Goodman & Leyden, 1991), improves feeling and attitudes (Moreland & Zajonc, 1982) and facilitates trust (Luhmann, 2000). Understanding this phenomena could provide a benefit in the design of m-commerce systems as it provides an additional insight into how we perceive the physical world and how it may affect our perception within the digital environment. This could not only improve m-commerce results but also address the development of any decision support system that aims to assist users in difficult situations. Whilst the results in this particular area are not necessarily irrefutable they do, for the reasons discussed above, warrant further investigation as part of future work in this area.

As previously mentioned 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, so as a contextual label it could be misleading; is it describing a strenuous activity over a short time or a lighter activity over a longer period? Either way the person could be feeling exhausted at the end of the activity. The participant were encouraged to provide a subjective level of recent activity, however 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. The results show 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. As a disruptive context the level of activity as perhaps the most important context explored. Not only did activity stand out as an individual context that affected the relationships between affective state and

the cognitive phenomena explored, but it also accentuated the effect of other disruptive contexts upon these relationships. Also seen is that this effect is particularly apparent for users of mobile devices; this aligns with this research's hypotheses in a number of ways.

The influence of contexts upon mobile device users demonstrates that they are subject to a far more complex set of situational contexts. The increase in range of contexts this includes when compared to a larger device in an office or at home is obvious. Not only are mobile devices used within these environments but they are relied upon to a greater extent when the user is on the move. While this suggests that the range of environments is much larger, it is easy to ignore that the range of situations in each environment can also be much larger too. For example environments outside the typical use of a desktop PC will introduce elements of unfamiliarity in terms of both people, places and tasks, and produce an increased potential of unfamiliar distractions and physical activity.

Understanding the complexity of mobile user activity is paramount if this research is to be taken further. Not only does the device user rely upon a wide range of device applications for completing certain tasks they will also undertake these tasks within different physical situations. For example a user may choose to answer a text message whilst continuing an activity, e.g. walking in a shopping arcade, or they may choose to ignore it until much later. The time duration between the physical activity and use of the device could also be of importance. The mobile user could have immediate access to the device if they have it on their person whilst undertaking more strenuous activity, e.g. going for a run. If they choose, for example, to answer the phone mid-run their conversation could take a very different turn when compared to how it could potentially be if they returned the call once they are rested and at home. It is well documented that physical exercise is good for body but also for improving cognitive capability. Erikson et al. (2015) summarise that physical activity and levels of fitness improve brain health and cognitive performance in children and older adults. Prakash et al. (2015), also suggest that further research is required to understand the dose-response relationship between duration and intensity of physical activity with improved cognitive capacity. Most efforts within this area of research have focused upon the long term effects and benefits of physical activity upon cognition. However this research provides an insight into the immediate cognitive capacity

during or following a range of activity levels. The findings herein provide new insight into the relationship between activity and some cognitive processes that could further these areas of research. The stimulating effect of current or recent physical activity could indeed be key to understanding mobile-device users and their level of engagement, however the results may be due to longer term behaviours and an exploration of this notion seems pragmatic.

The above discussion demonstrates that the use of simple labels to describe a wide variation of situational contexts can potentially be an issue when attempting to describe a complex model. I now posit that the use of a descriptive word to label a context unintentionally presents misleading information to the reader because our minds automatically attach information based upon our preconceptions. Where a descriptive label is used for identifying a context it is understandable that we may associate additional information to it, or actually ignore important information that should be associated with it. For example, where the label 'location' is used as a context to describe the longitude and latitude, as an individual we may attach additional information on the physical environment and past experiences. However it is valid to also state that there are several locations that can be applied to a context with a label of, say, 'shopping'. It is an issue of semantics. The use of context is complex and a detailed acknowledgment should always be made in recognising what the contextual model does and does not attempt to do.

6.6 Disruptive Context and Recommender Systems

The measurement of contexts and achieving context-awareness is by no means a new concept. Context such as time and location are well established as essential components for many context-aware systems. Electronic tourist guides are a prime example of where these contexts have been applied, knowledge of the user's location is simple to establish through various smart-device sensors, e.g. GPS and WiFi (Gavalas & Kenteris, 2011), and is an obvious benefit to many potential systems. Singularly, the use of location as a context-aware system is superficial and additional information is required to become effective – simply recommending all the Points of Interest in a surrounding location will overload the user with options. The personalisation of the recommender system to

recognise preferences or behaviours establishes a far more usable platform. Observing actions over time can obtain understanding of habits and interactions with people and the environment (Yurur et al., 2016). While knowledge of routines and functional status of a person can provide insight into elements of cognitive behaviour, e.g. focusing on a task, this information may not provide the depth required to determine additional cognitive behaviours as addressed in this research.

The ability to understand elements of cognitive capacity that form, for example, levels of decision capability, will support the development of several areas of research. Yurur et al., (2016) state that the influence of human related context within Social Network Platforms is an "exciting research topic". CenceMe (Miluzzo et al., 2007) attempt to use user relevant activities, temperament, habits and surrounding information in Social Network Platforms and observe that the logging of location, activity and conversations were popular features, however some participants did not like functionality that was outside their control and turned off certain features (Miluzzo et al., 2008). This suggests that transparency is important and that the ability to assess and address concerns of privacy should always be paramount when using sensitive, private information.

Coupling achievements such as these together with this research output provides Social Network Platforms the option to potentially gain an in-depth understanding of an individual's capacity for engagement. While this as a proposition comes with its own ethical concerns it would allow advertisers on these platforms to personalise further their marketing material because of the knowledge of engagement likelihood and preferences available. While this prospect may seem alarming to some I propose that the information provided by the context-aware system should be abstracted. In other words instead of providing every nuance of contextual information to other parties the data could be presented as an abstracted case e.g. by stating that the user is 'experiencing high dominance and they are surrounded by distractions and unfamiliar people', or the input to the Social Network Platform could be abstracted further to mirror the existing SiDISense output, i.e. 'The user has high potential of purchase engagement'. This as a method requires further research but demonstrates how important the use of a SiDISense-like system could become within a commercial context.

This research has relied heavily upon the user's subjective opinion of their environment's distractions to inform levels of purchase-decision involvement and information perception. This is a novel concept as while distractions have been considered in previous research their effect has typically focused upon an actual disruption of a task as it is undertaken, whereas this research has attempted to act as predictor of cognitive capabilities before the task is even considered by the participant.

Research into the issues of environmental distractions has primarily focused upon their impact on work and learning activities. Distractions to the knowledge worker are acknowledged as a prime issue that prevents tasks being completed effectively (Parnin & Görg, 2006). While previous work has attempted to use recommender systems to filter out distractions that cause delay in completing tasks or aid the re-finding of previously accessed information, it is reliant upon contextual information to be effective (Sappelli, Verberne, & Kraaij, 2017). However, not only could a context-aware recommender system use pre-filtering so that only specific information that is suitable to the task's completion is recommended (Sappelli et al., 2017) 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.

Other areas where distractions, including level of noise, is an issue is the impact that it has on a learner's concentration. A context recommender that focuses upon activities that access previously learnt knowledge rather than learning new material would be more successful when distractions are higher (Verbert et al., 2007). This approach aligns itself with this research's findings, however they note that prototypes have only previously focused upon measurement of noise and knowledge of specific locations. Our approach to modelling multiple disruption types and their impact on a user may support a more refined tool for supporting learning within a mobile context.

While this research has focused upon understanding of disruptions at a certain point it has not given consideration to disruptions over time. Anhalt et al., (2001), investigates opportunities that could minimise distraction levels and categorise distraction types ranging from *Snap*, a few seconds, to *Extended*, a long term need to change the task. While I acknowledge the usefulness of this

categorisation of distraction, it is not enough to judge the duration of the potential impact on the task. The user's cognitive capacity, affective state and other situated contexts must be considered. However, temporal dimensions could provide insight into user ability to withstand the effects of a particular distraction and provide further insight into the bearing of other contexts. Acknowledging the time frame of a distraction will no doubt support the development of a more realistic model for assessing the impact that disruptions can have upon tasks.

The depth of insight that this research provides is potentially of benefit in addressing the problem areas discussed above. However, I also see the benefit of adapting this research to produce an insightful model of situational disruptions and envisage a positive impact upon other research problem areas where implementation of recommender systems is an option.

6.7   Classification of Disruptive Contexts

In addition to the main research focus in demonstrating relationships between situational contexts and cognitive processes, the aim was to develop a context-aware prototype that could demonstrate its value in determining an ideal option for engaging a potential consumer. With disruptive contexts having been shown to impact the cognitive–affective state relationship an ANN algorithm was used to develop classifiers for the two most important disruptive contexts identified. Both 'user activity' and 'environmental distractions' were selected to represent situational disruptions.

The final SiDISense system developed as part of this research was an Android application that ran in the background on the experiment participant's personal smart-phone device. The system measured both level of activity, using the on-board accelerometer, and level of distractions using the phone's microphone in an attempt to classify aspects of disruptive context. The key aim of the system was however to show that a context-aware system would be able to identify higher levels of purchase-decision involvement and levels of information perception for it to then determine an engagement process. This demonstration was achieved by using a process of logic that alternated between an always advertising, i.e. non-context aware, and advertise as per the resulting suggestion delivered by the context-aware system. Alongside the classification system developed, the context-aware logic was

established through the capture of subjective feedback from the user on affective state (PAD), disruptive contexts (distractions, activity) and cognitive processes (purchase-decision involvement and perception of information).

While capturing user subjectivity was suitable for determining a relationship between cognitive behaviour and affective state, I must acknowledge that this is not particularly rich in detail. This lack of depth in contextual detail could be why the classification process for the context of *level of activity* in the final experiment only achieved a 59.34% success rate. Using a simple high or low reading of activity, it seems probable that a larger training set could improve results as the initial training results produced much higher success than the final experiment. However, additional training instances may also reduce the classification success if individual users' levels of subjectivity is not a focus, therefore learning individuals' behaviours may be required. Other reasons for the inferior performance, when compared to the classification of distractions which achieved 77.48% success, could include the measurement of the accelerometer data over the relatively long time-span of fifteen minutes. Kwapisz et al., (2011) used short periods of ten seconds as a time frame to recognise actual movement types, e.g. running, walking. Therefore is it possible that measuring shorter periods together with the accumulation of readings to establish an indication of level of activity over a longer period would be a better representation. Similarly, while the results of classifying the level of distractions were considerably higher than for activity it is still probable that the notion of distractions could have benefited richer context by including complementary sub-context information such as visual and physical details. As already detailed above the distractions manifest themselves in different ways and not all rely upon noise to become apparent. Categorising distractions within different groups to then test their effect upon relationships between cognitive behaviour and affective state would benefit a system that required a greater depth of understanding.

Both the activity and distraction classifiers produced better results within the previous training/testing phase when compared to the final live experiment's output. From the results it is possible to suggest a number of possible options that could be considered to improve the success of live classification of contexts. The most immediate solution would be to complete further research into ensuring the

selection of features in the training set is appropriate to increase the performance of the classifier (Panda et al., (2012). Increasing the training set whilst ensuring that the training data is also scenario rich could also be a benefit to the success of the classification process (McDonald, 2001). This would either require a larger, naturally achieved dataset, or a number of scenario based experiments to collect additional data. In addition to these possible options I have previously highlighted two additional possible routes worth pursuing. Applying additional and related contexts together will essentially create a better understanding of the main goal, for example by measuring not only the amount of physical activity but also the location, time and even the purpose of the activity, an increase in the completeness in the situation's measurement would be achieved which in turn could enhance its effectiveness in determining the response behaviour. Also of benefit to classification success could be the utilisation of unsupervised adaptive classification for learning over time on an individual's device (Lu et al., 2009).

Context duration is also a key factor for understanding context – disruptions or user activities are often determined by length of time. Activities tend to last 10 seconds or more and indeed can last considerably longer (Lu et al., 2010). Distraction on the other hand can be constant, short in duration or intermittent. This suggests that while there have been many successes in classifying activities, the capturing and measurement of the wide range of distractions will be more problematic. While this research maintained a reasonable level of classification for measurement of distractions using the microphone (77.48% success rate) a more dynamic model may be required to achieve greater success. Understanding the environment contexts, e.g. location, task etc., could then be used to adjust the time span used to identify related disruptions.

One of the issues with sensing context via a smart-device is the actual device. These can vary in specification quality, but also how the device is used or even the way the device is held by the user can differ from user to user. If the microphone is used to determine a level of distraction it is probable that different readings could be achieved within the same environment. This is obviously problematic, however one method previously used which would help address this issue is pooling. This is used to increase classification success by the sharing of classifier models to other devices in close proximity

which could then pool their resulting inferences to achieve the most appropriate result (Emiliano Miluzzo et al., 2010).

From the results in earlier cycles of this research some discrepancies were observed, i.e. the effect of disruptive contexts upon relationships between affective state and cognitive processes is not always consistent. Some of these inconsistencies could be due to the above scenarios described where additional contexts are either reducing or enhancing the effect of the contexts in focus, in other words situations are more complex that just simple three way relationships that have been introduced in this research. This highlights that as the modelling of disruptive scenarios increases in complexity, and as the additional contexts are being introduced, the method of using rule-based logic to determine behaviour will be impractical. Fuzzy logic may be beneficial in its ability to model the effects of contexts to produce an output by using approximation (Zadeh, 1988), however this would still require an expert to support the development of the model's rules. It is more probable that machine learning algorithms will be required to classify scenarios either using ANN or similar algorithms that can implicitly detect complex nonlinear relationships (Tu, 1996). An ANN using Reinforcement Learning may in particular lend itself to this problem as it supports learning and maps actions to situations based upon interactions with the environment (Kaelbling, Littman, & Moore, 1996). Measuring a high number of contexts via the device and mapping these to the resulting user behaviour could potentially develop, over time, a user specific model that will benefit user engagement in m-commerce.

To summarise I suggest that my approach in the classification of disruptive contexts at this stage is purposely unsophisticated but is relatively effective and does demonstrate the proposed concept outlined in the introduction chapter, (see Chapter one). There are, however, many previous works available from which to extend to a more detailed and inclusive model of classification to further this work. This research's main goals was to identify the relationships between contexts therefore this approach is prudent because it demonstrates a classification model at a foundation level without the complexities of multi-faceted classification.

6.8   Review of Methodology

The process of using self-administered questionnaires for capturing survey data is an established method that is relied upon within many research areas. While best practice is not always adhered to there are several controls that should be utilised to help ensure validity and reliability of the results are maintained (Kirk & Miller, 1968). The primary focus is the data itself, confidence in the sampling process and the repeatability of the results. These are critical, otherwise observations made become refutable. As noted in the Analysis and Results chapter (See Chapter five) the final experiment's datasets were somewhat skewed towards an older female group. However in this research's experiments overall this was not such an issue. From the analysis of all datasets there is no indication of age or gender forming patterns in the data which would impact on the research findings. Therefore I am confident that the distribution of the datasets is sufficient from which to draw conclusions.

The survey design structure did not change throughout this period of research. The stepwise process of presenting each of the self-administered questionnaires in a particular order, i.e. PAD, situational contexts, and then product involvement / information perception, was deemed fit for purpose from the start and having received no negative feedback or other concerns was adhered to throughout. The survey design followed the hypothetical steps that an autonomous system would follow. The user's affective state and situational contexts would be measured before the decision process regarding the product is attempted. Capturing the PAD reading straight away also ensured that this was not affected by the subsequent questionnaires, e.g. a potential change in emotions while the survey was undertaken. Measuring PAD again after the completion of the main elements of the survey may have provided additional insight however this could have impacted upon the participant's perceived workload and thus reduced the likelihood of continued engagement. Also as this was not a key focus of the research this additional level of data capture was not included.

This research analysis relied primarily upon correlation analysis, to indicate potential relationships. While causality cannot be suggested through this method, through careful consideration and presentation of logical arguments, a potential conclusion for a causal relationship can be suggested

(Simon, 1954). Relying upon modelling relationships developed via correlation analysis can be refuted in terms of causality because a third criterion for causality can be the actual cause of the correlation achieved. While it is not explicitly suggested, for example, that a high level of dominance leads to a high level of purchase-decision involvement, the results have demonstrated that it is likely that different levels of disruptive contexts are contributing to the correlations found. For example, where disruptive context levels were low no correlation between user dominance and purchase-decision involvement levels were found, however when disruptions increased a correlation was formed which suggests that a three way relationship exists, i.e. the development of the relationship between affective state, cognitive capability and disruptive contexts. It is can also suggested that because similar experiments were undertaken over the course of several research cycles, the results followed a relatively consistent pattern and this provided evidence that an appropriate study design had been achieved and a process for careful data collection followed.

To ensure that the correlation analysis undertaken was valid best practice was followed by implementing probability p-value calculations to demonstrate that findings were of significance. Using the findings to produce a rule-based model the effectiveness of using a context-aware system over a non-context-aware system was demonstrated. To test the null hypothesis that the sample population means are the same the Two Independent Sample T-Test was used to demonstrate probability significance. This exercise not only provided evidence that the use of the context-aware logic was more effective but also provided additional weight to the arguments developed that relationships exist between user affective state and cognitive behaviours, i.e. purchase-decision involvement and perception, especially where disruptive contexts are found to be of a high level.

The use of existing measurement scales for product involvement and purchase-decision involvement provided a sound foundation from which to make the hypotheses. In particular they provide a mind-set towards a product and not a decision making response behaviour (Mittal, 1989). This enabled us to capture both the participant's involvement with a product and also whether they were able to engage in a purchase decision at a stage where no decision making is required of the participant. This is an important note as it complements the research undertaken in user perception of product information

which obviously is an assessment of part of the decision making process which occurs at a later stage of the user's engagement.

Measurement of these 'existing' mind-sets could have led to static results as indicated in some of the early results that included larger devices and relatively static situations. However by then focusing upon the use of mobile devices it was possible to see more dynamic results which were attributed to the variance of the situational contexts that the participants were subject to as they went about their daily lives. The realisation that disruptive contexts were contributing to the relationships forming between the user's affective state and their level of purchase-decision involvement proved to be an exciting area on which to develop.

As expected a strong relationship between product involvement and purchase-decision involvement was found. As these are both, to some extent, situated measures it is important to note that product involvement endures the increase in disruptive contexts. This aligns itself with previous findings that state that a significant part of product involvement is enduring and reflects permanent view of the product (Bezençon & Blili, 2010). It is also apparent from the results that product involvement is also important in determining the level of purchase-decision involvement. Where levels of product involvement are low there are also low levels of purchase-decision involvement, however higher purchase-decision involvement results are achieved as affective state and the disruptive contexts intensify. This underlines the importance of considering disruptive contexts when determining likelihood of user engagement. For example while we would expect a user with a low product involvement for a particular product to always form a low level of purchase-decision involvement, this is not always the case. The results show that where user dominance is low then the purchase-decision involvement is indeed very low, however where user dominance is high then there is a stronger probability of a higher level of purchase-decision involvement being formed. This effect suggests that as long as dominance is high then we are still likely to form high levels of purchase-decision involvement even if we haven't previously shown a high level of product involvement for the product. If this is correct then this potentially changes the current method of e-commerce and

recommender systems which primarily focus upon estimating levels of product involvement rather than the proposed use of purchase-decision involvement.

The output of this research in understanding levels of user perception of information presented via a mobile device can be measured on several levels. The use of the *eab-perception* semantic differential tool enabled the measurement of a user's overall perception of product information presented using a number of styles e.g. detail processing, mental imagery, fear appeal etc. Through this tool it was possible to quickly capture the user's feedback without seriously impacting upon their perception of workload increase. This supported the requirement in requesting the participant to complete the survey a number of times.

The implementation of context-awareness within the experiment enabled us to ascertain when different information presentation styles were effective or not. For example, the use of mental imagery as a presentation style was suggested to be more effective when activity was high and dominance was low whereas where dominance was increased, mental imagery became less effective. While I had aspired to be able to demonstrate that a particular presentation style could be selected over another to ensure the best method of engagement possible within certain contexts, the method of implementation in the final experiment made it difficult to categorically say that this is possible. While testing the context-aware logic upon previously collected datasets post final experiment it was possible to demonstrate that a particular perception style worked better depending upon the user's affective state, behavioural and environment contexts. However, I could not fully demonstrate that one style over another would perform better in a similar scenario.

The primary reason for emphasising this point is to highlight that the majority of instances utilised the use of detail processing because of the relatively limited contextual scope for effective use of mental imagery. In other words the occurrence of situations where mental imagery was most effective was a lot smaller when compared to situations that benefited the detail processing presentation style. While this may seem limiting in terms of output success, the system's use of context-awareness logic did demonstrate an increase in the average eab-perception when selecting to either use detail processing

or mental imagery as alternative options in response to the situational contexts present. This does not categorically indicate that mental imagery did not perform better than detail processing or vice versa, just that the design of the final experiment did not cater fully for this level of detail.

The outcome of this section of the research is that it was possible to demonstrate that the use of context-awareness enables a system to know when a particular style will work or not and therefore provide the option as to whether to select to place the advert. It also demonstrates that the eab-perception tool was effective in measuring user perception within the context of this investigation. The methodology followed enabled the collection of findings which support further the value of understanding the impact of context on a person's cognitive capacity. With this understanding not only can an m-commerce system, e.g. a context-aware recommender system, benefit the commercial entity by providing likely user perception of a specific product advert, but it could also benefit the user experience in general. A context-aware m-commerce system will potentially improve the quality of the advert being recommended as the context will suit the cognitive preference at a certain time. It could potentially reduce the number of adverts being presented in times when situations prevent an appropriate response to the advert's content, i.e. a low chance of positive engagement. This as a concept could potentially reduce advertisement spend and also improve the user experience through reduced exposure to the constant marketing of products and services that is currently the norm.

6.9 Chapter Summary

This chapter has presented in detail the findings achieved through conducting this research. As a discussion chapter it has reviewed these findings and has detailed their meaning and their effect. It has highlighted the novel outputs of this research and has discussed limitations of the work completed. Also discussed has been the opportunities available to develop this research further both within the focus area of e-commerce and additional research areas that would benefit similar implementation of context-aware systems, primarily recommender systems. The chapter has also reviewed the methodology and tools used within the research, reflecting upon the effectiveness of the overall processes followed. The following chapter, Chapter seven, provides a summary of this research which

includes the objectives and the contributions made. Further work is also discussed before a final concluding statement is made.

7. Summary and Conclusion

7.1 Introduction

This chapter summarises the argument put forward within this thesis and the experiments conducted to demonstrate the hypotheses developed. In summarising the aim of the investigation and the contributions made, this chapter situates the work within a wider e-commerce context with a user cognitive-environment situational focus.

The aim of this investigation, as presented in chapter one, was to demonstrate a smart, context-aware system that provided a qualifying stage for use with existing e-commerce systems, e.g. recommender systems. The utilisation of a context-aware system was intent in providing a weighting factor that indicated the likelihood of engagement with the product placement which could then inform an e-commerce system. This was ultimately achieved through the identification of user behaviours and the investigation of relationships between affective state and situational contexts. These relationships were then modelled and demonstrated in the form of a context-aware system that improved upon existing non-context-aware systems. The system developed also implemented real-time classification of specific situational contexts to demonstrate somewhat the system's potential within a commercial context.

The research methodology followed a quantitative approach relying upon statistical measures to inform the development and subsequent testing of cognitive models that were implemented as part of the context-aware system. Surveys in the form of self-administered questionnaires were used throughout to gather participant data. The questionnaires were primarily measurement tools from existing research that were used to demonstrate affective-cognitive relationships. The discovery of novel behaviours was achieved through the development of the disruptive context questionnaire. This approach focused this research upon disruptive situational contexts which highlighted apparent extremes of these affective-cognitive relationships which could then be used to develop a model for engaging with mobile device users in terms of capturing likelihood of engagement.

The knowledge demonstrated through the introduction of disruptive contexts and their novel effect on the affective-cognitive relationship ensured the development of a context-aware method that proved superior to a non-context-aware approach to product placement. The following sections detail how the objectives were addressed and then presents the resulting contributions made within this research. Following this is a summary of suggested future work before a final concluding statement is made.

7.2   Summary of Objectives

This section is a summarisation of how the aims and objectives presented in the introduction chapter (Chapter one) were addressed. It provides insight into the decision processes involved and the steps taken to achieve the final output.

To conduct this work and establish a model of behaviour based upon user affective state and situational contexts a number of existing measurement models were used, these provided a set of previous research findings on which to build. Before considering the effects of environmental contexts and user physical behaviours it was important to obtain knowledge of specific consumer behaviours as a means through which situational effects could be demonstrated. This research aimed to develop a system that supported existing e-commerce processes, e.g. recommender systems, by providing a 'pre' state which could be utilised before the process fully engaged. To be able to do this an in-depth understanding was required of phenomena that shaped consumer behaviour. Chapter two provided an analysis and evaluation of relevant literature pertaining to online user behaviour within an e-commerce context. The chapter also discussed, in detail, the importance of user Affective State, i.e. mood and emotions, and its relationship with consumer behaviour. The literature also identified indicative research that suggested that relationships between the user's behaviour and their environment existed which could be used to develop a behavioural model.

With regards to the measurement tools used for identifying user interaction likelihood with an e-commerce advert or a purchase recommendation, the following tools were selected. The tried and tested Purchase-Decision Involvement measurement tool, (Mittal, 1989), was selected because it was specifically developed to measure a consumer's mind-set rather than a behaviour manifested in the

decision making process. In other words it identifies the benefit to the user through a specific product purchase and is not based upon any interaction i.e. a response behaviour. As this mind-set is a cognitive behaviour that reflects a user's preference even before a decision process is engaged. It was hypothesised that situational contexts could potentially affect the formation of this behaviour. Adopting this hypothesis enabled us to commence development of a preliminary stage that could be used before the main e-commerce engagement process was started.

In addition to the Purchase-Decision Involvement tool the literature also identified a number of consumer behaviours that could be manifested in certain presentation styles. A prime example is the use of fear appeal which is a complex advertisement style that utilises the transference of negative thoughts to the user in order to promote an action (Gardner, 1985). In an early experiment (section 4.2.1) I investigated a total of eight presentation styles, however the majority of the later work focused upon two common styles, mental imagery and detail processing. The use of these different styles was to establish whether a user's cognitive capability at a certain point in time could enable a system to determine which style was most suitable for productive user engagement. This as a method would further support the definition of a preliminary stage to inform the start of the engagement process. To do this a reading of user perception was needed. This was obtained using a short scale of semantic differentials developed to achieve a general reading of perception (see section 2.5.2).

The literature has previously identified that mood and emotions are directly related to cognitive phenomena (Calvo & D'Mello, 2010) – both purchase-decision involvement (Hansen, 2005), and perception of advertisements (Myers & Sar, 2015), demonstrate correlative relationships with user affective state. To be able to replicate and leverage these findings as part of this research it was required to use a technique suitable for use within an unobtrusive mobile context. Chapter two deliberated the benefit of dimensional models over other theories of emotion (section 2.2) and also the modelling of these theories within computing systems (section 2.3). Following this evaluation a decision was made to utilize the widely used three dimensional model of Pleasure, Arousal, Dominance, (Mehrabian, 1996), for capturing a concatenated reading of user affective phenomena (e.g. emotions, mood etc.).

As previously mentioned the tools above provided a platform on which to demonstrate user affective-cognitive relationships and to also develop a process for establishing the overall objectives (see Chapter three for implementation methods for the tools mentioned here).

Key to this research was the objective to develop an understanding of how our environment and our physical behaviour impact the affective-cognitive relationships. Again, chapter two presented analysis of physical contexts and introduced the notion of disruptive contexts and their effect upon cognitive behaviour. In section 2.6.2 hypotheses were developed that indicated that disruptive contexts including, levels of noise, distractions, physical activity and familiarity with people, all have potential to impact upon our cognitive behaviour. This research aligns with findings that particularly focused upon the use of smart devices and relationships with the user's environment. For example Holmes et al., (2014), determined that mobile device users are most likely to undertake consumer behaviours when they are at home, this being a familiar place where control over their environment is more probable.

From the literature review and early experimentation, the disruptive context questionnaire was developed (see section 3.7.4). As with the other measurement tools used in this research this self-administered questionnaire was implemented in a variety of ways ranging from paper format to bespoke Android application. Together these tools were implemented as surveys, with a total of seven experiments being completed. As detailed in chapter four, the disruptive context questionnaire was altered over the experimental iteration to focus on particular contexts of interest. However while fewer contexts were used in the final experiments I maintain that the overall model demonstrating the *affective state – cognitive process – disruptive contexts* relationship will present a more robust model for commercial use. The model developed supported the novel premise that would provide e-commerce systems, such as a recommender system, with a method in determining likelihood of engagement before attempting to implement the e-commerce activity, i.e. place the recommendation, and thus improve the effectiveness of the system.

The final objective was to develop a prototype software system that demonstrated the above model in a form that could be implemented on a mobile device. The development of SiDISense (Situational Decision Involvement Sensing System), was established over several iterations of a bespoke Android application developed by the author. SiDISense utilises the smart-phone's microphone and accelerometer to capture the contexts of recent physical activity and level of distractions within the user's immediate environment. Machine learning in the form of back propagation neural networks is used to classify these contexts in real-time with reasonable success. The software application developed alternated between the context-aware process, which determined whether to and how to place the advert, and a static system in order to collect discrete datasets which could then be assessed for similarity using statistical techniques.

This research relies upon statistical methods with correlative analysis being used throughout to identify relationships for developing the context-aware logic used by SiDISense. In the final cycle of experimentation to demonstrate the effectiveness of the model developed, the Two Sample T-Test was used to determine if the population means (context-aware and non-context-aware) are equal in order to assess the effectiveness of the context-aware system.

7.3 Summary of Contributions

The following section details the contributions achieved through this research. Concerned with the processes of e-commerce and appropriate use of contexts to improve the success rate of e-commerce engagement process, this thesis contributed to the following areas:

- A model was described and developed to represent mobile device users' cognitive capabilities for use as a system input before an e-commerce process attempts to engage with the user. The model was realised using the Android platform in the form of the SiDISense application developed for this purpose.

- The influence of situational context was explored with the resulting identification of key user context and physical situational contexts that influence mobile device users when forming attachment to, and perceptions of, product and service information on-line.

- The measurement of physical contexts using smart-device sensors and their classification using Machine Learning to enable realisation of context-aware system objectives in real-time without disrupting the device's performance.

The primary contribution of this work is the investigation into *affective state - cognitive process - disruptive contexts* relationships and the resulting context-aware model developed for improving the level of user m-commerce engagement. Using statistical analysis has demonstrated that it is possible to model user behaviour which demonstrates that the relationships between user affective state and specific cognitive behaviours are enhanced or decreased in their effect when disruptive contexts are present. Further to this it has been demonstrated that these models can be used to inform a context-aware system that requires insight into user behaviour. E-commerce recommender systems, for example, could benefit from insight into the likelihood of user engagement before making their recommendation of a product or service. The system could adjust the recommendation accordingly or even determine that any recommendation is not productive thus saving money and reducing the impact of unnecessary advertisements, for example, upon the user.

Following these developments the results demonstrate that a context-aware system could improve the average return, in terms of improved levels of purchase-decision involvement and improved perception of advertising styles when compared to a non-context-aware process, by an increase of up to 11.18% (see Chapter five). This demonstration was through the use of just two disruptive contexts, *activity* and *distractions*. It is expected that a significant increase in these results would be achieved as a more refined contextual model is developed. Nevertheless the existing improvement in performance achieved could in itself provide a substantial benefit to online commercial activities. The inclusion of additional disruptive context alongside traditional contexts that provide insight into user behaviours will ensure a powerful tool for the future.

In order to develop a realistic model suitable for use with user smart-devices several situational contexts were explored (see Chapter two). The notion and application of disruptive contexts quickly evolved upon the identification that these contexts act as stressors upon cognitive capabilities (see Chapter five). This development highlighted the importance of context-awareness in a novel way – previous work focuses upon the positive aspects of context whereas the term disruptive captures the concept that the effect of extremes of some contexts are an impediment to m-commercial activities.

Key to the development of the user engagement model was the inclusion of the device user's Affective State (an overall measurement of mood, emotions etc.). Modelling affective state in its three dimensional form reduced not only the assessment complexity found in emotional labelling but also simplified the process of capturing a complex phenomenon via a mobile device (see Chapter four). Also of importance is the corroboration of the value in using the dimension of user dominance. In fact as the primary factor in the engagement model for mobile device users, the dimension of dominance could be used as a standalone tool. This finding recognises a fundamental difference between mobile and static device users (see Chapter five) and also potentially simplifies the modelling of the affective state within certain m-commerce activities.

Also demonstrated is the use of Machine Learning, in the form of Artificial Neural Networks, for the measurement of the specific contexts key to the context-aware model developed (see Chapters four and five). Utilising both the smart-phone's microphone and accelerometer the contexts of activity and level of distractions were measured. This research identifies and discusses in detail the benefits and limitations of the process used (see Chapter six). The results however show that the approach was sound and provides a foundation from which to develop further the number of contexts used within the model and the accuracy of their classification in real-time.

Overall the research has demonstrated with success that through the utilisation of smart-phone technology it is possible to model elements of user behaviour. It also shows that this behaviour is reactional to its environment and therefore can be used to inform m-commerce activities. These activities currently rely upon knowledge of behaviour that inform preferences which can then be used

to shape recommendation in order to generate a greater likelihood of a purchase. This research is novel in that it has focused on the stage which immediately precedes the selection of the recommendation. Through the modelling of user environment interactions insight is provided into the user's cognitive capabilities. Results have demonstrated that this can be used to determine the potential success of the proposed recommendation and therefore increase the success rate of the e-commerce system involved. Having this additional layer of knowledge will further support the dynamic selection of products or services to considerably enhance the returns of m-commerce activities.

7.4   Recommendations for Further Work

The research undertaken for this thesis has identified a number of areas which would benefit further research in both the current theme and new areas of research. While some areas of the literature review were identified as requiring further detail, this is common and was addressed somewhat within the additional findings presented within chapter six. The outputs from the research have potential to support a number of areas, especially those that would benefit the use of a context aware system and provide insight into the cognitive capacity of the user. Knowledge workers or e-learners are two user bases which could benefit further work within this area. The main focus though is the implementation of e-commerce particularly within the mobile device domain. The following section details a number of recommendations, some of which have already been discussed in chapter six.

There are a number of areas covered in this research that would benefit additional research. The work completed thus far has highlighted novel concepts that were beyond the reach of the project to take further and reach a possible conclusion. The design of this research relied upon several existing measures which were used as a foundation on which to build. One of these in particular is well embedded within research. Mehrabian's (1996) three dimensional model of emotion, pleasure, arousal and dominance (PAD), proved to be a useful tool within this research with the dimension of dominance in particular leading to novel findings.

While many examples of the modelling of PAD exist there has been little attempt in developing an electronic representation through sensor measurement. Therefore a robust and accurate predictive model needs to be developed for a mobile platform. I suggest that further research is required to demonstrate an effective model that utilises on-board smart-phone sensors and applications to identify in real-time dimensions of PAD and in particular the dimension of user dominance. This will require a multimodal system that does not rely upon a singular method of classification – the accelerometer, microphone and camera have all been previously demonstrated as being useful for real-time classification. The benefits of this additional work will not only profit e-commerce activities but also other tools aiming to provide insight into psychological profiling. Of particular interest should be the inclusion of such a tool into the area of context-aware recommender systems. Not only would it support the novel concept for pre-recommendation analysis but also for capturing feedback within the decision making and consumption phases. Several commercial systems do exist in the traditional area of emotional feedback, see (Doerrfeld, 2016) for examples, however none, that I am aware of, focus upon dimensional space and favour the labelling of emotions and mood.

The other novel area identified which should attract further work is the notion of disruptive contexts. While context-awareness is relatively well defined, with many models in existence, this work is the first that has focused upon a collective that has been defined as disruptive to the device user. This research has identified a number of contexts that meet the criteria of disruptive effects, however the primary work has focused upon physical activity and environment distractions. Also identified is the effort required in the modelling of these contexts. Not only are they complex in themselves, their interaction with each other confounds the level of complexity further. While just using the two key contexts has produced significant results, the addition of further disruptive contexts will not only provide a more holistic model but also open other benefits of the technique in the future.

I finally suggest that together the recommendations above would complete the efforts undertaken within this research but would also present opportunities that could potentially address privacy concerns that many individuals currently have with their on-line data, in particular that which is held by social network platforms (Brookshire, 2017). While it is apparent that these platforms 'need' this

information to be able to undertake marketing exercises it is questionable to what extent our behaviours, moods and emotions should be so transparent and on so many platforms.

As additional data focused marketing processes are introduced to support e-commerce activities, concerns could potentially reach a point where an extended backlash could seriously affect current practices in e-commerce. As indicated in chapter six, section 6.6, it is recommended that methods of abstraction are investigated to minimise these concerns yet still maintain the key data that will enable marketing activities to take place effectively. It is possible that this could be a process that the user's device executes to which different services sign up to gain access to appropriate data, e.g. a level of 'likelihood of engagement', rather than a full suite of contextual information that is continually mined and not truly under one's control.

7.5   Conclusion

The aim of this research was to understand the complex and interrelated factors that constitute the relationship that mobile device users have with their environment. Understanding this relationship empowers mobile systems developers to generate predictive solutions where e-commerce can leverage user behaviour further than is currently the norm. The modern mobile smart-device certainly has the capacity to support smart activities, being armed with a suite of sensors and built in applications that can feed many aspects of context-awareness already utilised within modern e-commerce systems. Delving into consumer cognitive behaviours and their relationship with environment contexts and physical activity has provided further insight into the usefulness of context-awareness and has opened additional opportunities to explore.

This research has provided evidence that real-time capture of physical contexts is a realistic aim and has implemented a platform on which to develop further concepts pertinent to this project. It has also identified future work, with the need for realistic measurement of user affective state and in particular user dominance being paramount for the success of this method within the commercial arena.

The development of SiDISense and the demonstration of the effect of disruptive contexts has introduced a potentially powerful model that could empower the e-commerce community to deliver an increasingly realistic user-advert engagement process and also realise considerable returns through improved click-through-rates in the process.

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Appendix A: Involvement questionnaire

Questionnaire Consent Form

Project
 Situational influence on product involvement

SUPERVISORY TEAM

Dr Paul Sant, University of Bedfordhsire, Milton Kynes

Student Name

Mark Hooper, University of Bedfordshire, Luton

Questionnaire Purpose and Procedures

You are invited to take part in a research study. Before you decide to do so, it is important for you to understand the purpose of the research and what it will involve. Please take time to read the following information carefully. Ask me if anything is not clear or if you would like more information.
This research is designed to look at how a user interacts with on-line product information within different situational contexts. Findings will be deseminated via journal or conference publication and final project thesis.
If you decide to take part you will be given this information sheet to keep and asked to sign a consent form.
You are free to withdraw at any time without giving a reason. You also have the right to withdraw retrospectively any consent given, and to require that any data gathered on you be destroyed.
You are being asked to complete a questionnaire. We expect it will take you approximately 20 minutes to complete the questionnaire. Unfortunately there is no payment for taking part in this research.

CONFIDENTIALITY

Your identity will remain anonymous and will be kept confidential. Identifiable data will be stored securely for analysis, and then destroyed.
All data from participants will be anonymised in any research papers, reports, thesis documents, or presentations resulting from this work.

CONTACT INFORMATION ABOUT THE PROJECT

If you have any questions or require further information about the project you may contact
Mark.Hooper@beds.ac.uk

Ref: _____

Gender

Age

Please circle one

Please circle one

Male   Female

21 and Under   22 to 34   35 to 44   45 and over

Project

Situational influence on product involvement

Consent

We intend for your participation in this research to be pleasant and stress-free. ☐
Your participation is entirely voluntary and you may refuse to participate or ☐
withdraw from the study at any time.

1. I confirm I have read and understand the information sheet for the above ☐
    study and have had the opportunity to ask questions.

2. I understand that my permission is voluntary and that I am free to withdraw at any time, without
    giving any reason, without my legal rights being affected.

3. I agree to take part in the above study.

_____   _____   _____

Name of Participant   Date   Signature

_____   _____   _____

Name of Researcher   Date   Signature

Ref: _____

Mood Assessment

Select one image from each of the 3 rows that best represents your current feelings.
Pleasure vs. Displeasure The Pleasure Scale measures how pleasant an emotion may be. For instance both anger and fear are unpleasant emotions, and score low on the pleasure scale. However joy is a pleasant emotion and scores high. Select one image from the following row that best represents your current level of pleasure.
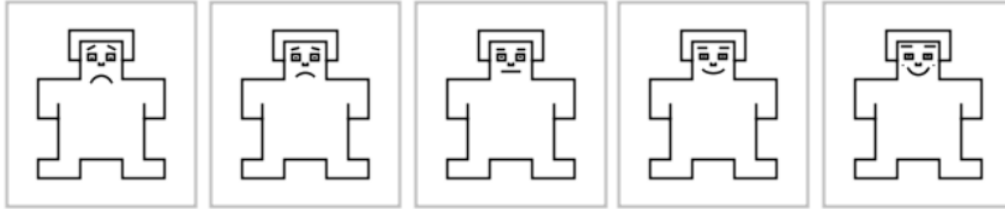
Arousal vs. Non-arousal The Arousal Scale measures the intensity of the emotion. For instance while both anger and rage are unpleasant emotions, rage has a higher intensity and scores very high on the arousal scale. However boredom, which is also an unpleasant state, has a low arousal score. Select one image from the following row that best represents your current level of arousal.
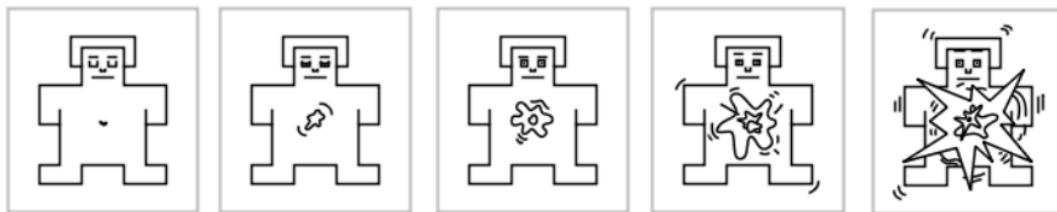
Dominance vs. Submissiveness The Dominance Scale represents the controlling and dominant nature of the emotion. For instance both fear and anger are unpleasant emotions anger scores high on the dominance scale, while fear has a low score. Select one image from the following row that best represents your current level of dominance.
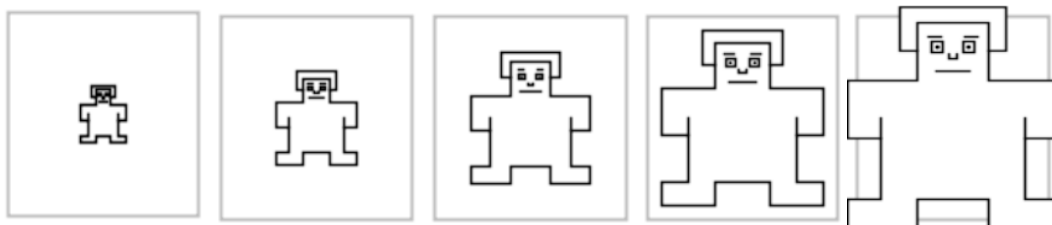
Your environment

Please rate each questing between 1 and 7 as best applies to you

1. Familiarity of your immediate environment

   Very unfamiliar / seems alien   1 2 3 4 5 6 7   Very familiar / somewhere I
   to me   go regularly

2. Level of noise in your immediate environment

   Very quiet   1 2 3 4 5 6 7   Very loud

3. Your amount of activity within the last couple of minutes

   None, I have been   inactive   1 2 3 4 5 6 7   High, I have been very   busy /

physical

4. How comfortable do you feel in your current surroundings?

I feel very   uncomfortable   1 2 3 4 5 6 7   I am relaxed in my
                                                                    surroundings

Tick the box if you are alone ☐ **otherwise please answer the following questions**

5. Number of people in your immediate vicinity

        I can see very few   1 2 3 4 5 6 7   It is far too crowded

6. Familiarity with people in your immediate vicinity

    Unknown to me   (strangers)   1 2 3 4 5 6 7   Well known to me   (loved
                                                                                           ones)

7. Current level of engagement / interaction with people in your immediate vicinity

        Not interacting at all   1 2 3 4 5 6 7   High level of interaction

Product-Level Involvement

Please rate each questing between 1 and 7 as best applies to you

1. _____ are very important to me.

        Strongly disagree   1 2 3 4 5 6 7   Strongly agree

2. For me _____ do not matter.

        Strongly disagree   1 2 3 4 5 6 7   Strongly agree

3. _____ are an important part of my life.

        Strongly disagree   1 2 3 4 5 6 7   Strongly agree

Purchase Decision Involvement

Please rate each questing between 1 and 7 as best applies to you

1. In selecting from the many types and brands of _____ available in the market, would you say?

I would not care at all as to which   1 2 3 4 5 6 7   I would care a great deal as to
        one I buy   which one I buy

2. How important would it be to you to make a right choice of this product?

Not at all important   1   2   3   4   5   6   7   Extremely important

3. In making your selection of this product, how concerned would you be about the outcome of your choice?

Not at all concerned   1   2   3   4   5   6   7   Very much concerned

Product information

Please rate each questing between 1 and 7 as best applies to you

1. When online and looking to purchase a _____ the *price and a known brand name* are very important to me.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

2. Product *styling, labelling and packaging* are important to me when purchasing a _____ online.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

3. Online *user feedback and ratings* of a _____ greatly influence my purchasing decision.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

4. *All product features* are important to me when purchasing a _____ online.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

5. *Only key product features* are important when purchasing a _____ online.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

6. I would compare information on *multiple products* when purchasing a _____ online.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

7. I consider *multiple sources* of information online before making a final decision when purchasing a particular _____.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

8. *Independent sources* of information placed within an e-commerce product page would influence me considerably when purchasing a _____ online.

Strongly disagree   1   2   3   4   5   6   7   Strongly agree

Appendix B: Recruitment Message

Hi

Can you please help with my research?

My project aims to show how our environment affects our level of decision involvement. Using the phone's accelerometer and microphone basic situational data is collected and analysed together with the questionnaire results. Note that the microphone only records while the questionnaire is being completed, so there is no intrusion into your privacy. Also note that all data collected is confidential, encrypted and secure. Consent is managed via the app.

Below is the link to the app (and more information on the project) on google play if you can participate it would be really appreciated.

https://play.google.com/store/apps/details?id=com.sidisense

Any questions please ask. Many thanks

Mark

PS: here's a bit more about the App

The app does take around ½ hour before asking any questions so don't worry if nothing happens straight away. The more times you answer the questionnaire the better results I'll get.

The App, Situational Decision Involvement (SiDiSense), analyses data from your phone's microphone and accelerometer as part of a research project into basic situational data. Together with this a questionnaire is used to capture user feelings and level of product involvement. This data is used to assess user decision processes within different user situations.

Using the App:

Please note that the more times you complete the questionnaire the better chance the project has of success. Please don't uninstall the app straight after completing the questionnaire as it take a couple of minutes before it uploads to the secure server.

Please note the following:

* The accelerometer is used to capture phone movement which is interpreted as level of user activity

* The microphone is used to capture background sound which are interpreted as distractions, please note recordings are not listened to or kept

* Machine learning algorithms are used to determine levels of both user activity and environment distractions. These processes are completed on the phone and raw data is not saved on the system or remote server

* The app will upload the files automatically to the server but this take a few minutes so please wait before uninstalling the app.

For further information please contact: Mark.Hooper@beds.ac.uk

Appendix C: Advert styles - Google Forms

On-line purchase decisions

This short research questionnaire is designed to look at how we make decisions when purchasing on-line

If you can find the time it would be very much appreciated, especially if you can use your smartphone or other mobile device whilst away from your desk or sofa.

Please note that your response is completely anonymous.

Many thanks in advance.

Mark

Mark Hooper
University of Bedfordshire
Luton, UK

Mark.Hooper@beds.ac.uk

*Required

About You
Please select one from each list below

1. Your gender *
Mark only one oval.

◯ Male
◯ Female

2. Your age *
Mark only one oval.

◯ 21 and Under
◯ 22 to 34
◯ 35 to 44
◯ 45 and over

3. The device you are using *
Mark only one oval.

◯ PC
◯ Laptop
◯ Smartphone
◯ Tablet

4. Your location *
Mark only one oval.

◯ Home
◯ Work/College/University
◯ Travelling
◯ Retail store
◯ High Street/Shopping centre
◯ Out and about

Your Mood

Please choose one image from each of the 3 scales that best represents your current feelings.

Pleasure vs. Displeasure

The Pleasure Scale measures how pleasant an emotion may be. For instance both anger and fear are unpleasant emotions, and score low on the pleasure scale. However joy is a pleasant emotion and scores high. Select from the list that best represents your current level of pleasure.

1   2   3   4   5

5. What is your level of pleasure? *

Mark only one oval.

	1	2	3	4	5	
Feeling no pleasure at all	◯	◯	◯	◯	◯	Feeling a lot of pleasure

Arousal vs. Non-arousal

The Arousal Scale measures the intensity of the emotion. For instance while both anger and rage are unpleasant emotions, rage has a higher intensity and scores very high on the arousal scale. However boredom, which is also an unpleasant state, has a low arousal score. Select from the list that best represents your current level of arousal.

1   2   3   4   5

6. What is your level of arousal? *

Mark only one oval.

	1	2	3	4	5	
Not feeling aroused at all	◯	◯	◯	◯	◯	Feeling very aroused

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Dominance vs. Submissiveness

The Dominance Scale represents the controlling and dominant nature of the emotion. For instance while both fear and anger are unpleasant emotions anger scores and high on the dominance scale whereas fear has a low score. Select from the list that best represents your current level of dominance.

1   2   3   4   5

7. **What is your level of dominance** *
   Mark only one oval.

	1	2	3	4	5	
Not feeling dominant at all	◯	◯	◯	◯	◯	Feeling very dominant

You and your environment
Please rate each question between 1 and 7 as best applies to you

8. **Familiarity of your immediate environment** *
   Mark only one oval.

	1	2	3	4	5	6	7	
Very unfamiliar	◯	◯	◯	◯	◯	◯	◯	Very familiar

9. **Level of noise in your immediate environment** *
   Mark only one oval.

	1	2	3	4	5	6	7	
Very quiet	◯	◯	◯	◯	◯	◯	◯	Very noisy

10. **Amount of distractions in your immediate vicinity** *
    Mark only one oval.

	1	2	3	4	5	6	7	
None at all	◯	◯	◯	◯	◯	◯	◯	Lots of distractions

11. Your current (or very recent) level of physical activity *

Mark only one oval.

	1	2	3	4	5	6	7	
Very low	◯	◯	◯	◯	◯	◯	◯	Very high

12. Number of people in your immediate vicinity *

Mark only one oval.

	1	2	3	4	5	6	7	
I am alone	◯	◯	◯	◯	◯	◯	◯	It is far too crowded

13. Familiarity with people in your immediate vicinity

Ignore this question if you are alone
Mark only one oval.

	1	2	3	4	5	6	7	
Unknown to me (strangers)	◯	◯	◯	◯	◯	◯	◯	Well known to me (loved ones)

Product Involvement

Please rate each question between 1 and 7 as best applies to you

14. Smartphones are very important to me. *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly disagree	◯	◯	◯	◯	◯	◯	◯	Strongly agree

15. For me smartphones do NOT matter. *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly disagree	◯	◯	◯	◯	◯	◯	◯	Strongly agree

16. Smartphones are an important part of my life. *

Mark only one oval.

	1	2	3	4	5	6	7	
Strongly disagree	◯	◯	◯	◯	◯	◯	◯	Strongly agree

Advert 1

Please look at this advert, do you think it is:

- Effective - successful in portraying the product

- Appealing - the advert makes the product appeal to you

- Believable - you believe what the advert is portraying

- Compelling - you think the advert can influence your actions

Sim Free Smartphone - black
⭐⭐⭐⭐☆ (254 customer reviews)
£150
You Save:£50.00

3G talk time 12 hours

1.2 GHz Qualcomm Quad Core Processor

5.0 inch IPS capacitive touch screen

Dual Cameras, front 1.3MP, back 8.0MP

8 GB Internal memory

Support memory card up to 64GB (NOT included)

Roll over image to zoom in

Dimensions (mm) 140 x 72 x 8.6

17. **How effective do you find this advert?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very ineffective	◯	◯	◯	◯	◯	◯	◯	Very effective

18. **How appealing do you find this advert?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very unapealing	◯	◯	◯	◯	◯	◯	◯	Very appealing

19. **How believable do you find this advert?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very unbelievable	◯	◯	◯	◯	◯	◯	◯	Very believable

20. **How compelling do you find this advert?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very uncompelling	◯	◯	◯	◯	◯	◯	◯	Very compelling

18. How appealing do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unapealing	◯	◯	◯	◯	◯	◯	◯	Very appealing

19. How believable do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unbelievable	◯	◯	◯	◯	◯	◯	◯	Very believable

20. How compelling do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very uncompelling	◯	◯	◯	◯	◯	◯	◯	Very compelling

Advert 2

Please look at this advert, do you think it is:

• Effective - successful in portraying the product

• Appealing - the advert makes the product appeal to you

• Believable - you believe what the advert is portraying

• Compelling - you think the advert can influence your actions

Sim Free Smartphone - black

★★★★☆ (254 customer reviews)

£150

You Save:£50.00

Imagine using this powerful, stylish smart-phone which is as durable as it is elegant.

It offers 3G, super-fast processing speed, 8 meg-apixel camera and a long-lasting battery at an affordable price.

Whether you want to listen to music while browsing the web, stream movies while updating your social networks, or run multiple apps while you're on a call, this phone will keep up with you.

21. How effective do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very ineffective	◯	◯	◯	◯	◯	◯	◯	Very effective

22. How appealing do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unapealing	◯	◯	◯	◯	◯	◯	◯	Very appealing

23. How believable do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unbelievable	◯	◯	◯	◯	◯	◯	◯	Very believable

24. How compelling do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very uncompelling	◯	◯	◯	◯	◯	◯	◯	Very compelling

Advert 3

Please look at this advert, do you think it is:

- Effective - successful in portraying the product

- Appealing - the advert makes the product appeal to you

- Believable - you believe what the advert is portraying

- Compelling - you think the advert can influence your actions

Sim Free Smartphone - black

⭐⭐⭐⭐☆ (254 customer reviews)

£150

You Save:£50.00

Smartphones have more sensitive personal data and are more vulnerable to security threats than your PC!

Using the latest technology our new smartphone platform has security services enabled as standard.

Get piece of mind with built-in apps that protect you from viruses and malware, you also have additional security options such as anti-theft and remote data recovery.

25. How effective do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very ineffective	◯	◯	◯	◯	◯	◯	◯	Very effective

26. How appealing do you find this advert? *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unapealing	◯	◯	◯	◯	◯	◯	◯	Very appealing

27. **How believable do you find this advert?** *

Mark only one oval.

	1	2	3	4	5	6	7	
Very unbelievable	◯	◯	◯	◯	◯	◯	◯	Very believable

28. **How compelling do you find this advert?** *

Mark only one oval.

	1	2	3	4	5	6	7	
Very uncompelling	◯	◯	◯	◯	◯	◯	◯	Very compelling

Appendix D: High involvement purchase decisions - Google Forms

High involvement purchase decisions

This short research questionnaire is designed to look at how we make decisions when purchasing high involvement products e.g. laptops.

If you can find the time it would be very much appreciated, especially if you can use your smart-phone or other mobile device whilst going about your daily lives.

You can submit as many responses as you wish.

Please note that your response is completely anonymous.

Many thanks in advance.

Mark

Mark Hooper
University of Bedfordshire
Luton, UK

Mark.Hooper@beds.ac.uk

*Required

About You
Please select one from each list below

1. **Your gender** *
   Mark only one oval.

   ◯ Male
   ◯ Female

2. **Your age** *
   Mark only one oval.

   ◯ 21 and Under
   ◯ 22 to 34
   ◯ 35 to 44
   ◯ 45 and over

3. **The device you are using** *
   Mark only one oval.

   ◯ PC
   ◯ Laptop
   ◯ Smartphone
   ◯ Tablet

4. **Your location** *
   Mark only one oval.

   ◯ Home
   ◯ Work/College/University
   ◯ Traveling
   ◯ Retail store
   ◯ High Street/Shopping centre
   ◯ Out and about

Your Mood
Please choose one image from each of the 3 scales that best represents your current feelings.

Pleasure vs. Displeasure

The Pleasure Scale measures how pleasant an emotion may be. For instance both anger and fear are unpleasant emotions, and score low on the pleasure scale. However joy is a pleasant emotion and scores high. Select from the list that best represents your current level of pleasure.

5. **What is your level of pleasure?** *
Mark only one oval.

	1	2	3	4	5	
Feeling no pleasure at all	◯	◯	◯	◯	◯	Feeling a lot of pleasure

Arousal vs. Non-arousal

The Arousal Scale measures the intensity of the emotion. For instance while both anger and rage are unpleasant emotions, rage has a higher intensity and scores very high on the arousal scale. However boredom, which is also an unpleasant state, has a low arousal score. Select from the list that best represents your current level of arousal.

6. **What is your level of arousal?** *
Mark only one oval.

	1	2	3	4	5	
Not feeling aroused at all	◯	◯	◯	◯	◯	Feeling very aroused

Dominance vs. Submissiveness

The Dominance Scale represents the controlling and dominant nature of the emotion. For instance while both fear and anger are unpleasant emotions anger scores and high on the dominance scale whereas fear has a low score. Select from the list that best represents your current level of dominance.

7. **What is your level of dominance** *
Mark only one oval.

	1	2	3	4	5	
Not feeling dominant at all	◯	◯	◯	◯	◯	Feeling very dominant

You and your environment
Please rate each questing between 1 and 7 as best applies to you

8. **Familiarity of your immediate environment** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very unfamiliar	◯	◯	◯	◯	◯	◯	◯	Very familiar

9. **Level of noise in your immediate environment** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very quiet	◯	◯	◯	◯	◯	◯	◯	Very noisy

10. **Amount of distractions in your immediate vicinity** *
Mark only one oval.

	1	2	3	4	5	6	7	
None at all	◯	◯	◯	◯	◯	◯	◯	Lots of distractions

11. **Your current (or very recent) level of physical activity** *
Mark only one oval.

	1	2	3	4	5	6	7	
Very low	◯	◯	◯	◯	◯	◯	◯	Very high

12. **Number of people in your immediate vicinity** *
Mark only one oval.

	1	2	3	4	5	6	7	
I am alone	◯	◯	◯	◯	◯	◯	◯	It is far too crowded

13. **Familiarity with people in your immediate vicinity**
Ignore this question if you are alone
Mark only one oval.

	1	2	3	4	5	6	7	
Unknown to me (strangers)	◯	◯	◯	◯	◯	◯	◯	Well known to me (loved ones)

When considering buying a smart-phone
Please rate each question between 1 and 7 as best applies to you

14. **In selecting from the many types and brands of smart-phones available in the market, would you say?** *
Mark only one oval.

	1	2	3	4	5	6	7	
I would not care at all as to which one I buy	◯	◯	◯	◯	◯	◯	◯	I would care a great deal as to which one I buy

15. **How important would it be to you to make a right choice of this product?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all important	◯	◯	◯	◯	◯	◯	◯	Extremely important

16. **In making your selection of this product, how concerned would you be about the outcome of your choice?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all concerned	◯	◯	◯	◯	◯	◯	◯	Very much concerned

17. If you had made a decision would you buy this product on-line right now? *

Mark only one oval.

	1	2	3	4	5	6	7	
Definitely not	◯	◯	◯	◯	◯	◯	◯	Most definitely

When considering buying a holiday

Please rate each question between 1 and 7 as best applies to you

18. In selecting from the many types and retailers of holidays available in the market, would you say? *

Mark only one oval.

	1	2	3	4	5	6	7	
I would not care at all as to which one I buy	◯	◯	◯	◯	◯	◯	◯	I would care a great deal as to which one I buy

19. How important would it be to you to make a right choice of this product? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not at all important	◯	◯	◯	◯	◯	◯	◯	Extremely important

20. In making your selection of this product, how concerned would you be about the outcome of your choice? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not at all concerned	◯	◯	◯	◯	◯	◯	◯	Very much concerned

21. If you had made a decision would you buy this product on-line right now? *

Mark only one oval.

	1	2	3	4	5	6	7	
Definitely not	◯	◯	◯	◯	◯	◯	◯	Most definitely

When considering buying a laptop computer

Please rate each question between 1 and 7 as best applies to you

22. In selecting from the many types and brands of laptop computer available in the market, would you say? *

Mark only one oval.

	1	2	3	4	5	6	7	
I would not care at all as to which one I buy	◯	◯	◯	◯	◯	◯	◯	I would care a great deal as to which one I buy

23. How important would it be to you to make a right choice of this product? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not at all important	◯	◯	◯	◯	◯	◯	◯	Extremely important

24. In making your selection of this product, how concerned would you be about the outcome of your choice? *

Mark only one oval.

	1	2	3	4	5	6	7	
Not at all concerned	◯	◯	◯	◯	◯	◯	◯	Very much concerned

25. **If you had made a decision would you buy this product on-line right now? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Definitely not	◯	◯	◯	◯	◯	◯	◯	Most definitely

When considering buying an insurance plan
Please rate each question between 1 and 7 as best applies to you

26. **In selecting from the many types and retailers of insurance plans available in the market, would you say? ***
Mark only one oval.

	1	2	3	4	5	6	7	
I would not care at all as to which one I buy	◯	◯	◯	◯	◯	◯	◯	I would care a great deal as to which one I buy

27. **How important would it be to you to make a right choice of this product? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all important	◯	◯	◯	◯	◯	◯	◯	Extremely important

28. **In making your selection of this product, how concerned would you be about the outcome of your choice? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all concerned	◯	◯	◯	◯	◯	◯	◯	Very much concerned

29. **If you had made a decision would you buy this product on-line right now? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Definitely not	◯	◯	◯	◯	◯	◯	◯	Most definitely

When considering buying a refrigerator
Please rate each question between 1 and 7 as best applies to you

30. **In selecting from the many makes and models of refrigerator available in the market, would you say? ***
Mark only one oval.

	1	2	3	4	5	6	7	
I would not care at all as to which one I buy	◯	◯	◯	◯	◯	◯	◯	I would care a great deal as to which one I buy

31. **How important would it be to you to make a right choice of this product? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all important	◯	◯	◯	◯	◯	◯	◯	Extremely important

32. **In making your selection of this product, how concerned would you be about the outcome of your choice? ***
Mark only one oval.

	1	2	3	4	5	6	7	
Not at all concerned	◯	◯	◯	◯	◯	◯	◯	Very much concerned

33. **If you had made a decision would you buy this product on-line right now?** *
Mark only one oval.

	1	2	3	4	5	6	7	
Definitely not	◯	◯	◯	◯	◯	◯	◯	Most definitely

34. **Many thanks for your participation**
Any comments?

_____

Appendix E: Screenshot - SiDiSense – Android Apps on Google Play

FAQ

Why is the microphone used? The microphone regularly records for one minute the background sound an algorithm then determines the level of distractions.

What does the accelerometer do? This just measures the phone's xyz movement and an algorithm is used determines the level of 'basic' activity.

How does the completed questionnaire get to the server? The app will upload the files automatically. If you un-install before uploading of files is completed your data will be lost so please check the process is complete before doing so by going to the main screen. If there are still files to upload you will be prompted.

For further information please contact: Mark.Hooper@beds.ac.uk

Your Privacy: Though the application requires permissions to your phone's sensors it does not record, monitor or store any personally identifiable information. Data that we do send to our secure server (i.e. questionnaire) is encrypted beforehand and is then only accessible to our research team explicitly working on this project.

Any data this app collects will remain private and will be encrypted and securely stored. You have the right to opt out of this research at any time by un-installing the application. You have the right to access any information related to you and request for any part of that data to be removed.

REVIEWS

Write a review

5.0
★ ★ ★ ★ ★
👤 6 total

★ 5   6
★ 4   0
★ 3   0
★ 2   0
★ 1   0

★ ★ ★ ★ ★
Quite interesting. If you have curious personality it will catch your attention.

★ ★ ★ ★ ★
:D

>

ADDITIONAL INFORMATION

Updated	Installs	Current Version
12 June 2017	100 - 500	1.4

Requires Android	Content Rating	Permissions
4.1 and up	PEGI 3	View details
	Learn more	

Report	Offered By	
Flag as inappropriate	Mark Hooper	

Developer
Email Mark.Hooper@beds.ac.uk
Privacy Policy

Appendix F: Screenshot - SiDiSense Privacy Policy

University of Bedfordshire

Computer Science and Technology

Search

CST Home

CST User Policy

Service Desk

Contact Us

Induction

Jobs and Open Days

Facilities and Support

Software and Resources

Opening Hours

Societies

Events

Hackathon

Global Game Jam

CompTIA

SiDiSense Privacy Policy

SiDiSense Privacy Policy

Project: Situational Decision Involvement (SiDiSense)

* Project Student: Mark Hooper
* Project Supervisor: Dr Paul Sant

Project Description

This app has been developed by researchers at the University of Bedfordshire, as part of ongoing research investigating how our everyday context (our environment, how we use the phone and our personal feelings) affects our behaviour towards information presented via a mobile device.

The project's android application, Situational Decision Involvement (SiDiSense), collects data from your phone's microphone and accelerometer as part of a research project into basic situational data. Together with this a questionnaire is used to capture a user's feelings and level of product involvement. The data collected is used to predict user decision levels within different user situations.

Please note the following:

* The accelerometer is used to capture phone movement which can be interpreted as level of user activity
* The microphone is used to capture sound to determine levels of noise and distractions only, recordings are not listened to
* The microphone ONLY records while the user completes the questionnaire and at no other time
* Both the accelerometer and microphone data collected by the current version of SiDiSense is analysed using algorithms on the phone and is not stored either on the phone or remote server

Privacy Policy

Your privacy is important to us: Though the application requires permissions to your phone's sensors it does not record, monitor or store any personally identifiable information. Data that we do send to our secure server is encrypted beforehand and is then only accessible to our research team explicitly working on this project. Data collected is not shared in any way.

Any data this app collects will remain private and will be encrypted and securely stored. You have the right to opt out of this research at any time by un-installing the application. You have the right to access any information related to you and request for any part of that data to be removed.

For further information please contact Mark Hooper at mark.hooper@beds.ac.uk

Lab Opening Times

Day	Hours
Monday	9:00am - 9:00pm
Tuesday	9:00am - 9:00pm
Wednesday	9:00am - 9:00pm
Thursday	9:00am - 9:00pm
Friday	9:00am - 9:00pm
Saturday	Closed
Sunday	Closed

Tweets by @UoBCST

UoB CST @UoBCST
Any students/alumni participating in Ludum Dare this year?
Jul 14, 2017

UoB CST @UoBCST
Well done Lukasz!
Jul 14, 2017

Embed   View on Twitter

SiDiSense Privacy Policy   Top ▲

Social/Community
Blogs
Facebook
Foursquare
Students' Union

The small print
Accessibility
Disclaimer
Equality
Sustainability

CST Labs
CST User Policy
Jobs
Facilities and Support
Software

Student Key areas
Student Gmail
BREO
Learning Resources
Timetables

Appendix G: Text - SiDiSense – Google Play and Privacy Policy

SiDiSense

Introduction

This app has been developed by researchers at the University of Bedfordshire, as part of ongoing research investigating how our everyday context (environment, phone use and personal feelings) affects our behaviour towards mobile information.

The App, Situational Decision Involvement (SiDi), collects data from your phone's microphone and accelerometer as part of a research project into basic situational data. Together with this a questionnaire is used to capture user feelings and level of product involvement. This data is used to assess user decision processes within different user situations.

Using the App:

Please note that the more times you complete the questionnaire the better chance the project has of success. Please don't uninstall the app straight after completing the questionnaire as it take a couple of minutes before it uploads to the secure server.

Please note the following:

* The accelerometer is used to capture phone movement which can be interpreted as level of user activity

* The microphone is used to capture sound levels which are interpreted as distractions, please note recordings are not listened to

* Machine learning algorithms are used to determine levels of both user activity and environment distractions. These processes are completed on the phone and raw data is not saved on the system or remote server

FAQ

Why is the microphone used? The microphone regularly records for one minute the background sound an algorithm then determines the level of distractions.

What does the accelerometer do? This just measures the phone's xyz movement and an algorithm is used determines the level of 'basic' activity.

How does the completed questionnaire get to the server? The app will upload the files automatically. If you un-install before uploading of files is completed your data will be lost so please check the process is complete before doing so by going to the main screen. If there are still files to upload you will be prompted.

For further information please contact: Mark.Hooper@beds.ac.uk

Your Privacy: Though the application requires permissions to your phone's sensors it does not record, monitor or store any personally identifiable information. Data that we do send to our secure server (i.e. questionnaire) is encrypted beforehand and is then only accessible to our research team explicitly working on this project.

Any data this app collects will remain private and will be encrypted and securely stored. You have the right to opt out of this research at any time by un-installing the application. You have the

right to access any information related to you and request for any part of that data to be removed.

SiDiSense Privacy Policy
Project: Situational Decision Involvement (SiDiSense)
Project Student: Mark Hooper
Project Supervisor: Dr Paul Sant

Project Description
This app has been developed by researchers at the University of Bedfordshire, as part of ongoing research investigating how our everyday context (our environment, how we use the phone and our personal feelings) affects our behaviour towards information presented via a mobile device.
The project's android application, Situational Decision Involvement (SiDiSense), collects data from your phone's microphone and accelerometer as part of a research project into basic situational data. Together with this a questionnaire is used to capture a user's feelings and level of product involvement. The data collected is used to predict user decision levels within different user situations.

Please note the following:
The accelerometer is used to capture phone movement which can be interpreted as level of user activity
The microphone is used to capture sound to determine levels of noise and distractions only, recordings are not listened to
The microphone ONLY records while the user completes the questionnaire and at no other time
Both the accelerometer and microphone data collected by the current version of SiDiSense is analysed using algorithms on the phone and is not stored either on the phone or remote server

Privacy Policy
Your privacy is important to us: Though the application requires permissions to your phone's sensors it does not record, monitor or store any personally identifiable information. Data that we do send to our secure server is encrypted beforehand and is then only accessible to our research team explicitly working on this project. Data collected is not shared in any way.
Any data this app collects will remain private and will be encrypted and securely stored. You have the right to opt out of this research at any time by un-installing the application. You have the right to access any information related to you and request for any part of that data to be removed.
For further information please contact Mark Hooper at mark.hooper@beds.ac.uk

Appendix H: SiDiSense Consent Management

Welcome to SiDi

The application, Situational Decision Involvement (SiDi), collects data from your phone's microphone and accelerometer in order to help determine the effect of basic situational data on decision processes. Any data this app collects will remain private and will be encrypted and securely stored.

You need to authorise the permission for recording audio otherwise the app will not work correctly. Please note that algorithms are used to determine levels of sound and the audio is not listened to by anyone.

You have the right to opt out of this research at any time by uninstalling the application. Only members of the research team will be able to access your data, and only for the purpose of conducting research. You have the right to access any information related to you and request for any part of that data to be removed.

This app has been developed by researchers at the University of Bedfordshire, UK. For further information please contact:

Mark.Hooper@beds.ac.uk

Agree & begin

Screenshot of welcome text which explains the process behind the application

This is your unique ID. You can find this under the management section if you, for any reason, wish to withdraw from the experiment

your id

Login to SiDi

Screenshot of page that presents the user an ID with instructions on where to find it again within the application if the user wants to withdraw from the experiment

Welcome
We need some basic information from you to be able to initiate the application

Gender
◯ Male
◯ Female

Age
◯ 21 and under
◯ 22 to 34
◯ 35 to 44
◯ 45 and over

Next

Screenshot of page that captures Initial demographic information before finalising the application background services
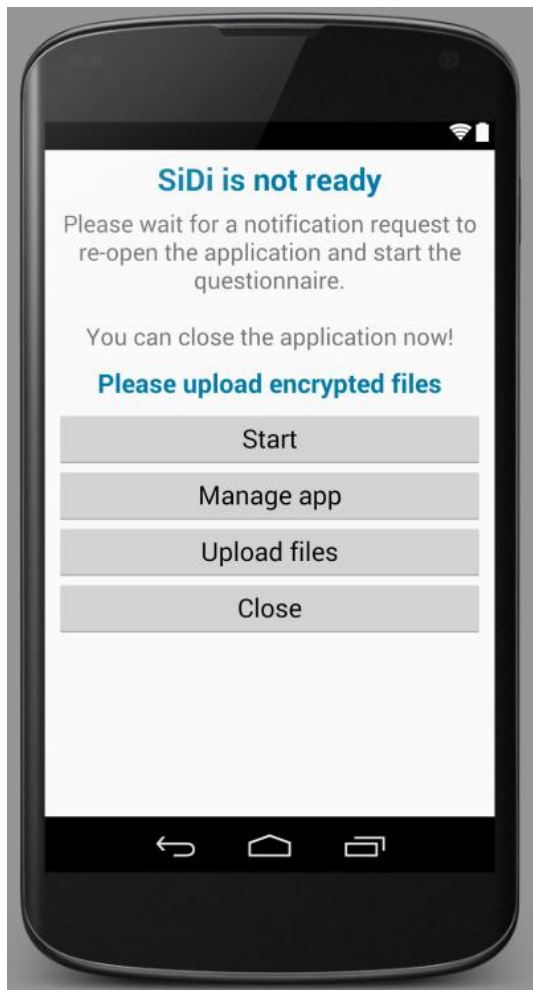
Screenshot of the main interface with dynamic instructions and button accessibility.
By clicking the 'Manage app' button the user can access the unique ID generated when the application is first opened

Screenshot of 'Manage user' interface which presents generated User ID and instructions on how to withdraw from the experiment.

Appendix I: RS1 Ethics Approved

UNIVERSITY OF BEDFORDSHIRE

Research Ethics Scrutiny (Annex to RS1 form)

SECTION A   To be completed by the candidate

Registration No: 99009115

Candidate: Mark Hooper

Research Institute: IRAC

Research Topic: Towards context-aware recommender systems within complex affective-environment relationships

External Funding: Self

The candidate is required to summarise in the box below the ethical issues involved in the research proposal and how they will be addressed. In any proposal involving human participants the following should be provided:

- clear explanation of how informed consent will be obtained,
- how will confidentiality and anonymity be observed,
- how will the nature of the research, its purpose and the means of dissemination of the outcomes be communicated to participants,
- how personal data will be stored and secured
- if participants are being placed under any form of stress (physical or mental) identify what steps are being taken to minimise risk

If protocols are being used that have already received University Research Ethics Committee (UREC) ethical approval then please specify. Roles of any collaborating institutions should be clearly identified. Reference should be made to the appropriate professional body code of practice.

It is expected that the following ethical issues need to be addressed:

1. **Involvement of vulnerable participants (Q1).** Own students would be included as test participants. Physical, social and psychological well-being will be ensured by conducting activities with integrity, respecting the rights and dignity of all participants.

2. **Involvement of intrusive interventions (Q6).** Physical exercise such as running is likely to be included in activity modelling. Participants will be requested to provide a doctors certificate with no participant being asked to go beyond comfort or ability when completing experimentation

3. **Data collection (security, confidentiality and anonymity).** There will be various methods of collecting personal data, mainly questionnaires and mobile phone use data. In both forms data will be collected anonymously using unique identification numbers. Paper questionnaires will be stored safely in a locked cabinet and when no longer required securely destroyed by using the approved University service provider. Electronic versions will be stored within a University approved secure network. Electronic data captured on mobile devices will be encrypted and deleted once no longer required.

4. **Obtaining consent.** Free and informed consent will be collected using a University approved consent form within an unpressurised environment with a cooling off period

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available.

5. **Purpose and dissemination**. A project brief together with a detailed presentation will be provided to prospective participants to explain the purpose of the project and data required, the methods to be used and the resolution to the ethical issues as addressed above in statements above.

6. **Communication and closure**: Where appropriate participants will be kept informed as to the progress of the research with feedbacks given to regarding the findings of the research

Answer the following question by deleting as appropriate:

1. Does the study involve vulnerable participants or those unable to give informed consent (e.g. children, people with learning disabilities, your own students)?
   Yes

2. Will the study require permission of a gatekeeper for access to participants (e.g. schools, self-help groups, residential homes)?
   No

3. Will it be necessary for participants to be involved without consent (e.g. covert observation in non-public places)?
   No

4. Will the study involve sensitive topics (e.g. sexual activity, substance abuse)?
   No

5. Will blood or tissue samples be taken from participants?
   No

6. Will the research involve intrusive interventions (e.g. drugs, hypnosis, physical exercise)?
   Yes

7. Will financial or other inducements be offered to participants (except reasonable expenses)?
   No

8. Will the research investigate any aspect of illegal activity?
   No

9. Will participants be stressed beyond what is normal for them?
   No

10. Will the study involve participants from the NHS (e.g. patients or staff)?
    * **No**

If you have answered yes to any of the above questions or if you consider that there are other significant ethical issues then details should be included in your summary above. If you have answered yes to Question 1 then a clear justification for the importance of the research must be provided.

*Please note if the answer to Question 10 is yes then the proposal should be submitted through **NHS research ethics approval procedures** to the appropriate **COREC**. The UREC should be informed of the outcome.

March 2011

Checklist of documents which should be included:

Project proposal (with details of methodology) & source of funding	X
Documentation seeking informed consent (if appropriate)	
Information sheet for participants (if appropriate)	
Questionnaire (if appropriate)	

(Tick as appropriate)

Signature of Applicant: *Mark Hooper*   Date: *05/12/2012*

P Saut

Signature of Director of Studies: Date: 07/12/2012

This form together with a copy of the research proposal should be submitted to the Research Institute Director for consideration by the Research Institute Ethics Committee/Panel

Note you cannot commence collection of research data until this form has been approved

SECTION B To be completed by the Research Institute Ethics Committee:

Comments: *The ethical issues have been identified and details provided.*

Approved

Signature Chair of Research Institute Ethics Committee:

Date: *19 Dec 2012*

This form should then be filed with the RS1 form

If in the judgement of the committee there are significant ethical issues for which there is not agreed practice then further ethical consideration is required before approval can be given and the proposal with the committees comments should be forwarded to the secretary of the UREC for consideration.

There are significant ethical issues which require further guidance

Signature Chair of Research Institute Ethics Committee:

Date:

This form together with the recommendation and a copy of the research proposal should then be submitted to the University Research Ethics Committee

March 2011

Appendix J: Revised Ethics approved Dec 2013

UNIVERSITY OF BEDFORDSHIRE

Research Ethics Scrutiny (Annex to RS1 form) - REVISED

SECTION A   To be completed by the candidate

Registration No: 99009115

Candidate: Mark Hooper

Research Institute: IRAC

Research Topic: Towards context-aware recommender systems within complex affective-environment relationships

External Funding: Department

The candidate is required to summarise in the box below the ethical issues involved in the research proposal and how they will be addressed. In any proposal involving human participants the following should be provided:

- clear explanation of how informed consent will be obtained,
- how will confidentiality and anonymity be observed,
- how will the nature of the research, its purpose and the means of dissemination of the outcomes be communicated to participants,
- how personal data will be stored and secured
- if participants are being placed under any form of stress (physical or mental) identify what steps are being taken to minimise risk

If protocols are being used that have already received University Research Ethics Committee (UREC) ethical approval then please specify. Roles of any collaborating institutions should be clearly identified. Reference should be made to the appropriate professional body code of practice.

The following ethical issues need to be considered:

1. **Involvement of vulnerable participants (Q1)**
    a. Own students would be included as test participants. However, this test does not request test subjects to undertake any activity other than having the Phone Application (App) installed on their phone and to answer a repeated short questionnaire when requested. Physical, social and psychological well-being is not forseen to be at risk.

2. **Data collection (security, confidentiality and anonymity)**
    a. Anonymised data will be collected via the App. Regular snapshots of data will be identified with a unique ID and then encrypted before being uploading to a secure server.

    b. File encryption is achieved using a combination of AES and RSA encryption methods. Server access is via an administrator username and password.

    c. Raw data will be deleted after a period of five years.

3. **Obtaining consent and withdrawing from the test**
    a. Free and informed consent will be collected via the App.

March 2011

b. Test subjects will be asked to provide consent to the test when the App is first started. Data collection will not be able to proceed without this consent being given.

c. Upon giving consent the test subject will confirm a unique account name (their gmail email account) this will be paired with a unique ID used to identify the test subjects data. This pair is saved to file and then encrypted before being uploading to a secure server.

d. The test participants can at any time withdraw from the test by uninstalling the App from their phone.

e. Test participants can request their data to be destroyed by submitting their account name to the administrator to remove any raw data associated with that account name.

4. **Purpose and dissemination.**
   a. A detailed brief will be available to prospective participants via the App's listing on Google Play store (see attached notes). It will explain the following:

      i. The purpose of the project and data required

      ii. The methods used to collect the data

      iii. The options for the test participant for withdrawing from the test and for deleting of their test data

5. **Communication and closure**
   a. Where appropriate participants will be kept informed as to the progress of the research with feedback given to regarding the findings of the research

Answer the following question by deleting as appropriate:

1. Does the study involve vulnerable participants or those unable to give informed consent (e.g. children, people with learning disabilities, your own students)?
   Yes

2. Will the study require permission of a gatekeeper for access to participants (e.g. schools, self-help groups, residential homes)?
   No

3. Will it be necessary for participants to be involved without consent (e.g. covert observation in non-public places)?
   No

4. Will the study involve sensitive topics (e.g. sexual activity, substance abuse)?
   No

5. Will blood or tissue samples be taken from participants?
   No

6. Will the research involve intrusive interventions (e.g. drugs, hypnosis, physical exercise)?
   No

7. Will financial or other inducements be offered to participants (except reasonable expenses)?
   No

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8. Will the research investigate any aspect of illegal activity?

No

9. Will participants be stressed beyond what is normal for them?

No

10. Will the study involve participants from the NHS (e.g. patients or staff)?

*   No

If you have answered yes to any of the above questions or if you consider that there are other significant ethical issues then details should be included in your summary above. If you have answered yes to Question 1 then a clear justification for the importance of the research must be provided.

*Please note if the answer to Question 10 is yes then the proposal should be submitted through **NHS research ethics approval procedures** to the appropriate **COREC**. The UREC should be informed of the outcome.

Checklist of documents which should be included:

Project proposal (with details of methodology) & source of funding	
Documentation seeking informed consent (if appropriate)	
Information sheet for participants (if appropriate)	
Questionnaire (if appropriate)	

(Tick as appropriate)

Signature of Applicant: _Marie Hooper_   Date: _16.12.2013_

Signature of Director of Studies: _P. Sant_   Date: 13/12/2013

This form together with a copy of the research proposal should be submitted to the Research Institute Director for consideration by the Research Institute Ethics Committee/Panel

Note you cannot commence collection of research data until this form has been approved

SECTION B To be completed by the Research Institute Ethics Committee:

Comments: _Point One is well addressed in the Obtaining consent form._

Approved ✓

Signature Chair of Research Institute Ethics Committee:

March 2011

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Date:

This form should then be filed with the RS1 form

If in the judgement of the committee there are significant ethical issues for which there is not agreed practice then further ethical consideration is required before approval can be given and the proposal with the committees comments should be forwarded to the secretary of the UREC for consideration.

There are significant ethical issues which require further guidance

Signature Chair of Research Institute Ethics Committee:

Date:

This form together with the recommendation and a copy of the research proposal should then be submitted to the University Research Ethics Committee

Caroline Lomas

From:	Dayou Li
Sent:	13 December 2013 16:27
To:	Caroline Lomas
Subject:	FW: Revised ethics form
Attachments:	Obtaining Consent - Context Monitor.docx; MHPS - EthicsFormSigned.pdf

Signed form will be with you on Monday.

Dayou

From: Mark Hooper
Sent: 13 December 2013 13:03
To: Dayou Li
Cc: Paul Sant
Subject: Revised ethics form

Hi Dayou

As per previous conversations, I have produced a new ethics form to cover the work Paul and I are currently doing. Not a big change but more focused on the current activities. I have used the RS1 ethics form, I hope ok.

Also attached is supporting document that details the consent process that we intend to follow. Please let me know if you have any questions or if I need to provide any other supporting information.

Many thanks.

Best regards
Mark

Google Play Online Listing - Snapshot
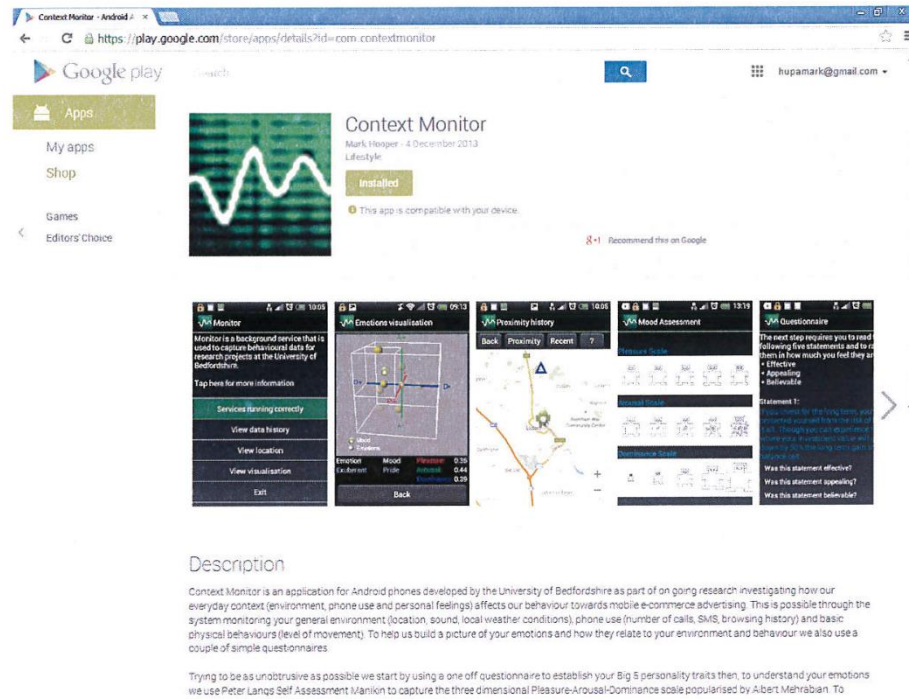
Google Play Online Listing - Details

Description

Context Monitor is an application for Android phones developed by the University of Bedfordshire as part of ongoing research investigating how our everyday context (environment, phone use and personal feelings) affects our behaviour towards mobile advertising. This is possible through the system monitoring your general environment (location, sound, local weather conditions), phone use (number of calls, SMS, browsing activity) and basic physical behaviours (level of movement). To help us build a picture of your emotions and how they relate to your environment and behaviour towards mobile advertising we also use a couple of simple questionnaires.

We start by using a one off questionnaire to establish your personality traits, whether you are male or female, your age and your ethnic background. To understand your emotions a self assessment manikin is used to capture your levels of pleasure-displeasure, arousal-sleepiness and dominance-submissiveness. To compliment this we also ask you to select specific labels that you associate with your current mood/emotions. Finally we ask you to review a set of five, randomly selected, statements that need to be rated for effectiveness, appeal and believable levels. This final section is

core to our research into developing an understanding of engagement with mobile advertising messages.

Your Privacy: Though the application requires permissions to your phone's sensors and activity logs it does not read or monitor any personal content whatsoever. It does not save any identifiable data to the phone and any data we send (using WiFi) to our secure server for analysis is encrypted beforehand. The data is then only accessible to our research team explicitly working on this project to determine how environment and personal feeling affect engagement to mobile advertising.

If you have any concerns, please contact us.

Consent Process on the Context Monitor Application

Step 1: Obtain Consent when first start using the App

Title:　　　　　　　Joining Context monitor

Text body:　　　　　Welcome to Context Monitor. This app collects data from your phone's sensors, including location, microphone and accelerometer. It also accesses your phone use logs including call's/SMS/browsing and other phone apps. We do not store any audio clips, telephone numbers or read any email/SMS content. Any data this app collects will remain private and will be encrypted and securely stored.

　　　　　　　　　　You have the right to opt out of this research at any time by uninstalling the application. Only members of the research team will be able to access your data, and only for the purpose of conducting research. You have the right to access any information related to you and request for any part of that data to be removed.

　　　　　　　　　　This app has been developed by researchers at the University of Bedfordshire, UK. For further information please contact Mark.Hooper@beds.ac.uk

Consent button:　　Agree & Begin

Step 2: Request Login once consent given

Title:　　　　　　　Login to Context Monitor

Text body:　　　　　Use your abcdef@gmail.com account to start using Context Monitor

**Login button:**　　　Login to Context Monitor

Appendix K: List of statements

#	Style	Text
1	low_risk	Our new product# AlphaTech# has outperformed market leaders far beyond expectations. The use of Cryin in our product prevents degradation and ensures long term stability and user effectiveness.
2	low_risk	Research has show that SuperS is the number one choice for domestic use. SuperS's superior formula also lowers wear and tear and ensures machine longevity.
3	low_risk	The patented SuperLite has 60% higher resolution than its nearest competitor# providing 20% higher resolution together with crisp text and images
4	low_risk	99% of households questioned use MiracleGlow in their daily cleaning activities (Which?# 2013)
5	low_risk	Justin from London says# "these gizmos are very popular at the moment# I've got two# everyone should have one!"
6	low_risk	The GizmoPro *****(98 customer reviews)
7	low_risk	Rare opportunity to buy a limited edition print by the popular artist Travo Pelensky. These are highly sought after by collectors and have held their value for the last decade. Following recent exhibitions around the world auction prices are expected to r
8	low_risk	Just about every Hollywood A-lister has invested in one of these new accessories# you too can look this good without breaking the bank
9	higher_risk	Between 85 and 90% of all new experimental drugs will fail# and not surprisingly most biotech stocks will also# eventually# fail. However there are significantly high rewards when things go right
10	higher_risk	Having a good understanding of the stock market can be very rewarding financially however underperformance is common and large amount of stocks fall# losing value long term.
11	higher_risk	If you invest for the long term# you've protected yourself from the risk of losing it all. Though you can experience times where your investment value will go down by 50% the long term gain should balance out.
12	fear_failure	Don't lose out! One day left on this offer
13	fear_failure	Your holiday voucher expires today# don't be stuck at home with this awful UK weather
14	fear_failure	Don't get ripped off# offer expires soon
15	fear_failure	Your system is at risk# free virus check available today only
16	optimistic_success	Book your trip to the beach and give yourself a memorable vacation next year
17	optimistic_success	Click here for future offers to get the best deal for your summer break

18	optimistic_success	Sleep easy when you protect your PC with monthly system checks as standard with all our products
19	mental_imagery	The fresh and juicy orange juice sat waiting on the breakfast # very cold and sweet# a great start to the day
20	mental_imagery	Run your hands on the soft satin fabric# it's going to be a peaceful sleep tonight
21	mental_imagery	The whiff of the aroma of the freshly brewed coffee drifted up the stairs# feel yourself tingle in anticipation for the first cup of the day
22	mental_imagery	The yolk was like the sun# the bacon its legs shimmering across the plate. With the golden butter melting on the hot toast# this had to be the perfect breakfast.
23	detail_processing	Unconcentrated orange juice with high pulp content is far better for you and just 100ml has been shown to be enough for one of your five a day requirements
24	detail_processing	Our fair trade coffee not only tastes great but you are supporting developing countries without any additional cost when compared to the majority of other household brands.
25	detail_processing	Cheapest English breakfast in town# egg# bacon and a slice of toast for just £3
26	detail_processing	Guaranteed for 5 years our satin bed sheets hold their colour and shape for 10 times longer than our closest competitor
27	positive_attitude	Saving a little out of every pound we bring home is the foundation of independence. The role of a house in our financial life is to build equity# we will use our home as a savings account and then we'll leave that equity safe where it is for the future.
28	positive_attitude	Your investment will increase over times even if there are dips in the market. Using your savings carefully you can expect good rewards.
29	positive_attitude	Looking after your new product you can have a long and productive experience.
30	negative_attitude	Without savings we can't build equity in our home# we can't invest for the future# and we can't be ready for challenging times.
31	negative_attitude	Without regular investment you won't achieve the safety net required for later life and can't expect a comfortable retirement.
32	negative_attitude	If you do not own this product you won't be able to be productive and shouldn't expect success.
33	low_effort	Enriched with natural herbal extracts our gentle formula reduces skin irritations.
34	low_effort	A revolution in sizing# fit and thinking. Slimming side seams & subtle boot cut flatter your shape.
35	low_effort	This rare Chinese tea is carefully picked by specially trained monkeys in a remote mountain region of China.

36	high_effort	Specifically formulated for those with hyper-sensitive skin# Phytomer Accept Neutralizing Cream uses calming ingredients to restore skin that has become irritated by harsh ingredients. The hypoallergenic formula of this sensitive skin care product has bee
37	high_effort	The most informative sensor data seem to be measurements of person to person proximity# and statistics of vocalization and body movement measurements. We present common architecture principles of context-aware systems and derive a layered conceptual design
38	high_effort	In contrast# a traditional survey of the same subjects produced only 54% agreement between subjects (where both subjects acknowledged having the conversation) and only 29% agreement in the number of conversations.

Appendix L: Writing style product formats (HTML/CSS)

Mental Imagery representation for bike product
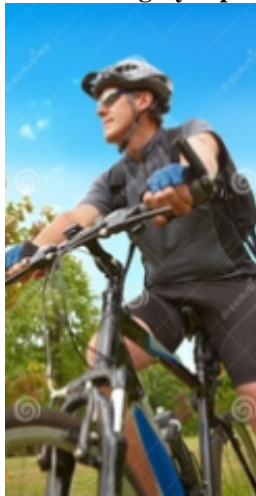
Detail Processing representation for bike product

HTML for Mental Imagery representation for bike product

```
<!DOCTYPE html>
<html>
        <head>
        <link rel ="stylesheet" type = "text/css" href = "style.css" />
        </head>
        <body>
            <div id="wrapper">
                <aside id="left">
                  <img src="img/bike.jpg" style="width:130px;height:250px;">
                </aside>
                <aside id="right">
                  <h1>Hybrid Bike Pro</h1>
                  <p class="top">Imagine starting an exciting adventure on your new lightweight, desirable hybrid
                  bike.</p>
```

```
          <p>Take a moment and visualise yourself in the open countryside on this stylish and modern bike
          knowing you are safe in the knowledge that you will not be let down by its high technology
          specification.</p>
          <p class="top"><img src="img/stars.jpg" style="width:60px;height:13.7px;">
          <span style="float: right; color:blue; font-size: 80%;">latest offers</span></p>
          </aside>
      </div>
  </body>
</html>
```

HTML for Detail Processing representation for bike product

```
<!DOCTYPE html>
<html>
      <head>
      <link rel ="stylesheet" type = "text/css" href = "style.css" />
      </head>
      <body>
        <div>
          <aside id="left">
              <img src="img/bike.jpg" style="width:130px;height:250px;">
          </aside>
          <aside id="right">
              <h1>Hybrid Bike Pro</h1>
              <ul class="top">
                 <li>Lightweight, smooth welded alloy frame</li>
                 <li>Carbon fibre fork for lightweight handling</li>
                 <li>1x11 speed groupset for smooth gear shifting</li>
                 <li>Centreline Rotors for controlled stopping power</li>
                 <li>Versatile disc brake rim for large-volume tyres</li>
              </ul>
              <p class="top"><img src="img/stars.jpg" style="width:60px; height:13.7px;"> <span style="float:
              right; color:blue; font-size: 80%;">latest offers</span></p>
          </aside>
        </div>
      </body>
</html>
```

CSS style sheet used for all product representations

```
body {margin: 0px;  }
h1, p, ul {font-family: verdana;}
h1 {margin: 0; color:#236B8E; font-size: 130%; }
p, ul {font-size: 120%; }
li{padding-bottom: 5px;  }
ul.top {border-top: 1px solid #ccc; padding-top: 5px; margin-top: 5px; }
p{ margin:0; margin-top: 5px;}
ul{ padding-left:20px;}
p.top { padding-top: 5px; margin-top: 5px; border-top: 1px solid #ccc; }
#left{ float: left; }
#right {margin-left:10px; width:35%;  float: left; }
.floatRight { float:left; font-weight: normal; }
```

Appendix M: Product advert text and images

Product	Image Used	Image URL (accessed March 2016)	Mental Imagery Advert Text	Detail Processing Advert Text
Airline ticket		http://cdn.skim.gs/image/upload/v1456339150/msi/isolated-plane-ticket_qhcgpn.jpg	**Airline Tickets** Imagine being able to search millions of flights and packages for cheap deals to thousands of destinations around the world. Take a moment and visualize yourself exploring exclusive offers, real time information on city breaks and last minute deals. We provide such easy to booking of cheap flights you will never forget your time with us.	**Airline Tickets** • Search over a million flights and packages • Easy to book cheap flights • Thousands of destinations around the world • Real time information about flight times • Exclusive offers, seat sales, and great deals • City breaks, last minute deals, airlines and flights
Bicycle		https://thumbs.dreamstime.com/t/man-riding-bike-25763541.jpg	**Hybrid Bike Pro** Imagine starting an exciting adventure on your new lightweight, desirable hybrid bike. Take a moment and visualise yourself in the open countryside on this stylish and modern bike knowing you are safe in the knowledge that you will not be let down by its high technology specification.	**Hybrid Bike Pro** • Lightweight, smooth welded alloy frame • Carbon fibre fork for lightweight handling • 1x11 speed groupset for smooth gear shifting • Centreline Rotors for controlled stopping power • Versatile disc brake rim for large-volume tyres

Books for education		http://www.topeducationdegrees.org/wp-content/uploads/2016/01/63577587560 01800821152486765_State-Education-Generic-jpg.jpg	**Teach Yourself Textbooks** Imagine starting to learn that subject that you've always wanted to succeed in. Take a moment and visualise yourself enjoying the self-paced tutorials in this well organised set of teach yourself textbooks. We guarantee that these are perfect for your busy lifestyle and that you'll never look back once you get started.	**Teach Yourself Textbooks** • Well-illustrated, full colour series of books • Carefully organized for busy learners • Self-paced tutorials for easy learning • Suitable for university courses • Case studies and analytical techniques with examples • Authors are highly respected within their fields
Broadband		http://www.ispreview.co.uk/wp-content/gallery/cache/2048__330x330_ fibre_optic_bt_boom.jpg	**New Broadband Deal** Imagine purchasing this amazing broadband deal. Take a moment and visualise yourself enjoying the superfast connection speeds to watch your favourite TV shows and sporting events. We will give you 33% off selected bundles and smash hit dramas that we know you'll love.	**New Broadband Deal** • Ultrafast speeds of up to 500Mbps • 6 months discounts with selected deals • Free connection with selected online purchases • Free TV packages & watch smash hit dramas • Free UK-based customer support • New customers get 33% off selected TV bundles
Car		https://media.ed.edmunds-media.com/bmw/5-series/2014/oem/2014_bmw_5-series_sedan_535i_fq_oem_9_1280.jpg	**Performance Coupe** Imagine upgrading to this incredibly stylish coupe. Take a moment and visualize yourself cruising the motorway and winding down local country roads in this high spec'd performance car that has incredibly low CO2 emissions. We'll give you a driving experience that you'll never want to swap.	**Performance Coupe** • 4.7L V-8 449hp engine twin turbo • CO2 emissions as low as 89 g/km • ECO Start/Stop technology • Active Parking Assistant with reversing camera • Electrically folding exterior mirrors • LED High Performance headlamps

Car insurance		http://www.cranerecoverymalappuram. com/wp-content/uploads/2015/04/PMNA-Crane-Recovery-Service-Insurance-Service.jpg	**Car Insurance** Imagine the peace of mind that comes with extensive cover that's personalised to you. Take a moment and visualize yourself with the satisfaction of full claims protection, 24/7 quick access to help when you need it and full protection if you have an accident with any uninsured drivers. We'll give you immediate cover so you can enjoy your driving experience from the word go.	**Car Insurance** • Uninsured driver promise • 24/7 claims line • Over £100 personal belongings cover • No claims discount and protection • Personalised cover - extras that suit you • Get immediate cover - comprehensive or 3rd party
Champagne		https://encrypted-tbn3.gstatic.com/images?q=tbn:ANd9 GcQtrBFFfPBK3ePlDrCJfFzQiRipEE GHKlt3b8FZ0SBqrKFaJK_P6Qpwc_ w	**Grand Cru Champagne** Imagine celebrating a special occasion with loved ones enjoying this classically blended champagne. Take a moment and visualize yourself enjoying this medium bodied Brut which benefits from over three years ageing to achieve an elegant palate. We'll give you a wine with impeccable heritage that you can enjoy at any occasion.	**Grand Cru Champagne** • Medium Bodied, Brut, 12.0 % alcohol • Sourced from the prestigious Grand Cru village of Mailly • Benefiting from over three years ageing • A classic blend of 75% Pinot Noir and 25% Chardonnay • A wine with an elegant palate, structure and finesse
Computer		https://encrypted-tbn2.gstatic.com/images?q=tbn:ANd9 GcTt4MO7oeTGxdUDtlZ4sZ9x8H5NJ ptVJW9Sxt0n8_99gfTAV5mdoSYfOw	**High Performance, Gaming PC** Imagine enjoying the ultimate gaming experience. Take a moment and visualize yourself playing your favourite games on this high performance water cooled gaming computer. We'll give you a lifetime evolution warranty so you'll never need to buy another PC again.	**High Performance, Gaming PC** • Water Cooled, Desktop Gaming PC • 3.6GHz Intel Quad Core Processor • 32GB of 1600MHz Gaming RAM • 120GB SSD + 2TB SATA-III Hard Drive • 4GB Advanced Dedicated Graphics Card • Lifetime Evolution Warranty Included

Cosmetics		https://encrypted-tbn1.gstatic.com/images?q=tbn:ANd9GcRqRkkDLN_PaFdKoGIb8QFtjMlj3xtkr5ZU3KSA_T6xGHIQ0VPkWyhzQos	**Branded Cosmetics - Lipbalm** Imagine showing off your lips and impressing your friends with this high pigmented lipbalm. Take a moment and visualize using this glossy and rich balm whilst shielding your skin from the sun's harmful rays. This product will give you piece of mind while you enjoy your fresh, new look.	**Branded Cosmetics - Lipbalm** • 3-in-1 lip tint with high pigmented performance • Creamy balm for a glossy and rich effect • Spectrum SPF 20 to shield from the sun's harmful rays • Packed with antioxidant-rich vitamin E • Nourishing formula moisturizes and smooths the lips
Fashion Clothing		https://www.getgof.com.ua/wp-content/uploads/2016/01/Debenhams-com-store-1.jpg	**Regular Fit Jeans** Imagine making an impact with these fashionably casual jeans. Take a moment and visualize ultimate comfort in these regular fit, distinctively faded 5-pocket jeans. These are a perfect accompaniment for a laid-back daytime style, it's time to enjoy a fresh, new look.	**Regular Fit Jeans** • Regular fit, straight leg cotton jeans • Casual style with studs and contrast stitching • Distinctive faded 5-pocket jeans • Denim weight 11.9 oz • 100% Cotton (leather label on waistband) • Machine wash 30°
Fridge		https://encrypted-tbn3.gstatic.com/images?q=tbn:ANd9GcSMbs1ggyCm8Q3UH-FVB7FsV0-OoJc0S_c622vg_Su4K4lv-ataRE7DvzI	**Retro Fridge Freezer** Imagine adding that special touch to your kitchen with this classically retro fridge. Take a moment and visualize saving money with this high energy efficient, high capacity fridge freezer that will also become a talking point with every admiring visitor to your home. The product is a perfectly funky yet functional addition to any modern kitchen.	**Retro Fridge Freezer** • Hygiene Protection • A+ Energy Rating • 100 Litre Fridge Capacity and 56 Litre Freezer Capacity • Energy efficiency performance rating: A • Super Freeze • Dimensions (HxWxD): 144 × 49.5 × 53.6cm

Health care		https://images.weedmaps.com/pictures/listings/395/184/441/large/1654727_bigstock-Middle-aged-doctor-pressing-mo-47648923.jpg	**Healthcare Insurance** Imagine the peace of mind that comes with comprehensive cover from a quality insurance provider of more than 25 years. Take a moment and visualize yourself with the satisfaction of knowing you have access to private medical treatment in a wide choice of UK private hospitals. We'll give you worry free cover at competitive prices.	**Healthcare Insurance** • Quality insurance for more than 25 years • Comprehensive range of plans at competitive prices • Prompt access to private medical treatment • Post-diagnostic treatment and therapies • Consultations, diagnostic tests, MRI, CT and PET scans
HiFi Stereo		https://encrypted-tbn3.gstatic.com/images?q=tbn:ANd9GcQTi2HNHRrrtf6b9ZL1Z7vLwsIH85J1ni59zeHODZ8_vEm8iKa2sZjrnzg	**Floor Standing HiFi System** Imagine a high quality, high tech listening experience. Take a moment and visualize yourself relaxing at home and enjoying your evenings with this elegant hi-fi system as a focus point of your music entertainment centre. With this high specification, classy looking system you'll be the envy of all your friends and family.	**Floor Standing HiFi System** • 70W tital power Crystal Amp Pro • EZ MP3 Maker via CD Ripper • Remote control with smartphone Bluetooth • Apple docking compatibility • Dimensions: 20 x 20 x 110 cm • Clock/Sleep/Timer Facility
Holiday		https://encrypted-tbn0.gstatic.com/images?q=tbn:ANd9GcQ6a3hf5Fc-GQs6G-sqHYauk7LUkiSb8fbgYZDgojhCjOEyUyA6Iv_6HQ	**Ultimate Beach Resorts** Imagine the ultimate beach destination. Take a moment and visualize breathtaking views, beautiful white sand beaches, crystal blue waters and an amazingly warm climate. We provide a great location perfect for a romantic retreat that also provides you with many activities to make this a great, family-friendly location as well.	**Ultimate Beach Resorts** • Beautiful white sand beaches and crystal blue waters • All hotels are beachfront properties, or overlooking the shore • Fully-equipped gym facilities widely available • Top 5 water sports: Dolphin safari, snorkelling, private speed boat excursions and catamaran sailing • Multiple 6-hole golf courses

Hotel		https://encrypted-tbn1.gstatic.com/images?q=tbn:ANd9GcTj6mX5RnwWvPPhZtzQku0P9K0yFJO21U0aWtuQtZmZmoBxzngJShAw9PY	**London's Top Boutique Hotel** Imagine the perfect city break hotel experience. Take a moment and visualize yourself in a deluxe room with a modern entertainment system set in a perfect setting to escape from it all or catch up with work. We provide a perfect location for you to relax, whether it's at our restaurant, the roof-top bar or our fully equipped fitness centre	**London's Top Boutique Hotel** • Deluxe Room with Flat screen TV, satellite channels (including sports) • Plenty of room to work at the desk with free standard WiFi • Large open-air rooftop bar known for its cocktails • Foreign Currency Exchange and multi-Lingual Staff • Fully-equipped, compact fitness centre
House		http://www.kingcompaniesusa.com/wp-content/uploads/2016/01/topdestination.jpg	**New Build Homes** Imagine living here in this large modern family home. Take a moment and visualize yourself and your loved ones moving into this wonderful, modern house with fully fitted kitchen and everything you need to enjoy your comfortable new surroundings. We provide a worry-free help to buy scheme while you focus on planning your future.	**New Build Homes** • Large, modern lounge 3.77m × 4.84m • Fully fitted kitchen including appliances • 5 double bedrooms, 2 family bathrooms, En-Suite • Large plot including garage & driveway • Help to buy scheme with just 5% deposit • 10 year warranty
House insurance		http://www.loansexpert.co.in/wp-content/uploads/2016/12/home-loan--380x205.jpg	**House Insurance** Imagine the peace of mind that comes with home insurance designed to provide maximum security. Take a moment and visualize yourself comfortable in the knowledge that you have extensive cover that protects you and your home. We'll give you a complete service so you don't have to worry about possible accidents or emergencies of the future.	**House Insurance** • Unlimited buildings insurance • Contents insurance up to £100,000 • ID fraud detection and assistance • Personal possessions and accidental damage cover • Family legal protection • Home emergency cover up to £500

Jewellery		https://s3-media1.fl.yelpcdn.com/bphoto/daEBM589dz7Jbd_fvGF3bQ/258s.jpg	**Brilliant cut diamond necklace set** Imagine yourself or a loved one positively glowing whilst wearing this amazing necklace set. Take a moment and visualize taking out of the box for the first time these beautiful diamonds set in 18k white gold, knowing just what an impact they'll make. We provide unique, fully certified jewellery that really helps you impress.	**Brilliant cut diamond necklace set** • 100% Natural Diamonds • Durable, high gold content 18k White Gold • 28.03 carat certified G/VS2 • Complimentary EDR Certificate • Free gift box and packaging • Free next day delivery on all orders
Laptop		http://pcsupport.lenovo.com/gb/en/products/Laptops-and-netbooks/Yoga-Series/yoga-500-14ibd	**11.6 Inch TouchScreen Laptop** Imagine enjoying a combination of versatility, performance, and style with this compact new laptop. Take a moment and visualize the convenience of quick and seamless switching between a laptop, tablet, or presentation screen that meets your varying requirements and gives you a quality user experience.	**11.6 Inch TouchScreen Laptop** • Intel Celeron processor N3050 • 4GB DDR3L Memory / 500GB Hard Driver • LCD 10-point multitouch screen • Intel HD Graphics, Bluetooth 4.0 interface • Built-in HD Webcam / WLAN (802.11b/g/n) • 360° hinge / Weighs only 3 lbs
Life insurance		http://www.insuranceschool.org/wp-content/uploads/2016/12/life-insurance-415x260.jpg	**Life Insurance** Imagine the peace of mind that comes with simple, jargon free insurance. Take a moment and visualize yourself with the satisfaction of knowing you have provided your family protection in the event of anything serious happening to you. We'll give you worry free cover at competitive prices.	**Life Insurance** • Access to highly competitive life cover quotes • No obligation to buy • Independent from any particular insurer • We consider all existing medical conditions • Life insurance plans made simple and jargon free • Quick, simple service

Mobile phone		https://encrypted-tbn1.gstatic.com/images?q=tbn:ANd9GcQTU4VBJ8xUwucfzi6MfCrjdW_uykq9DoQnZR41gikh9amyZwYdchxH7w	**Sim Free Smartphone** Imagine using this powerful, stylish smartphone. It offers 3G, super-fast processing speed, 8 megapixel camera and a long-lasting battery at an affordable price. Visualise yourself listening to music while browsing the web, streaming movies while updating your social networks, or running multiple apps while you're on a call. This phone will keep up with you.	**Sim Free Smartphone** • 3G talk time 12 hours • 1.2 GHz Qualcomm Quad Core Processor • 5.0 inch IPS capacitive touch screen • Dual Cameras, front 1.3MP, back 8.0MP • 8 GB Internal memory • Support memory card up to 64GB
Sofa Furniture		https://www.willowandhall.co.uk/media/catalog/product/cache/1/image/85e4522595efc69f496374d01ef2bf13/f/o/foxham_4.jpg.jpg	**Luxury Fabric Sofa** Imagine relaxing in this comfortable and stylish sofa. Take a moment and visualize spending quality time with your family and friends as they admire the new focal point of your home. This product gives you a perfect seating experience that you'll never forget.	**Luxury Fabric Sofa** • Retro inspired range with distinctive curved silhouette • Filling Fibre-wrapped foam seat, fibre back. Frame, glued and stapled • Removable legs, suspension serpentine springs • 10 year guarantee with Multiyork Stainguard protection • Dimensions H90 x W176 x D98cm
Instant video streaming		http://wpmedia.business.financialpost.com/2015/10/1022ipad.jpg?quality=60&strip=all&w=620	**Instant video streaming** Imagine the pleasure of your evenings with unlimited streaming of movies and TV episodes. Take a moment and visualise yourself enjoying the superfast connection speeds to watch your favourite TV shows and films. We will give you a competitively priced, versatile service that will really improve your TV watching experience.	**Instant video streaming** • UK unlimited streaming of movies and TV episodes • Supports internet-connected TVs, Blu-ray players and set-top boxes • Full membership free for a month for new customers • Access more than 15,000 movies and TV episodes • High dynamic range content and Ultra HD streams, no extra cost

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Television		https://transmitter.ieee.org/wp-content/uploads/2015/06/uhdcurve.jpg	**Curved 78-Inch HD 3D Smart TV** Imagine a high quality, high tech TV watching experience. Take a moment and visualize yourself relaxing at home and enjoying your evenings with this 78 inch smart TV as the focus point of your home entertainment. With its high specification and large, curved screen you'll be the envy of all your friends and family.	**Curved 78-Inch HD 3D Smart TV** • 78-Inch Smart TV / Smart Remote Control • Refresh Rate: 120CMR (Effective) • Backlight: LED • UHD Dimming and auto Depth Enhancer • Built-in WiFi 802.11ac, 4 HDMI ports • Two pairs of 3-D active glasses
Washing machine		http://scoophub.in/wp-content/uploads/2016/01/bosch-washing-machine.jpg	**1200rpm Freestanding Washing Machine** Imagine low cost and efficient washing machine performance. Take a moment and visualize yourself a quick and easy clothes washing routine, smaller bills and greater leisure time. This product provides large drum capacity and multiple programming that meets all your needs.	**1200rpm Freestanding Washing Machine** • 6KG Capacity • 1200rpm Spin Speed • 15 Programmes including a quick wash • Energy efficiency performance rating: A+ • Washing Performance: A • Dimensions (cm) 85 (H) x 59.5 (W) x 47 (D)

Appendix N: Java implementation of Weka libraries

The full implantation of the Weka libraries utilise Java Swing components which are not compatible with Android implementation of Java classes / libraries. Therefore it is essential to utilise the stripped version of Weka which is available here https://github.com/shamtastic/Weka-Stripped

The same stripped version of Weka must be used for both the Java and Android applications otherwise there will be incompatibility issues when transferring classifier files to the Android implementation.

Three Java classes are presented below:

1. Process – this class processes the data files to produce Weka compatible files that are used for training and testing undertaken via the NNetwork class. The Process class uses the Statistics class to convert the raw data into features.

2. Statistics – this class is used to produce the mean and the standard deviation of a sample of data i.e. a window within the file

3. NNetwork – this class relies upon Weka algorithms to classify and test the data produced

```
import java.io.BufferedInputStream;
import java.io.BufferedReader;
import java.io.ByteArrayOutputStream;
import java.io.File;
import java.io.FileInputStream;
import java.io.FileNotFoundException;
import java.io.FileOutputStream;
import java.io.FileReader;
import java.io.IOException;
import java.io.PrintWriter;
import java.util.ArrayList;
import java.util.List;
import java.util.Locale;
import java.util.Random;

public class Process{

        public static void main(String[] args) throws IOException, InterruptedException{

                int percentage =25; // percentage for election of test files
                String dir = "................................/soundfolder/" ;      // location of data

                File folder = new File(dir);
                File[] listOfFiles = folder.listFiles();

                // sample sizes
                int allFiles = listOfFiles.length;
                int sampleNumber = (int)(listOfFiles.length*(percentage/100.0f));
                int numOfTrainingFiles = listOfFiles.length - sampleNumber;

                // produces file lists for training and testing
                String [] testData = new String[sampleNumber];
                String [] trainingData = new String[numOfTrainingFiles];
                String [] allData = new String[allFiles];

                int countTest = 0;
                int countTrain = 0;
                int countAll = 0;

                Random r = new Random();
```

```java
                // make list of testing files
                while(countTest < sampleNumber) {
                        System.out.println("Making test file " + (countTest) +"\n");
                        String temp = listOfFiles[r.nextInt(listOfFiles.length)].getName();

                        boolean notInList = true;
                        for(int j = 0; j < sampleNumber; j++) {
                                if(temp == testData[j]) {
                                        notInList = false;
                                }
                        }
                        if(notInList) {
                                testData[countTest] = temp;
                                countTest++;
                        }
                }

                // make list of training files
                while(countTrain < (numOfTrainingFiles)) {
                        System.out.println("Making Train file " + (countTrain) +"\n");
                        String temp = listOfFiles[r.nextInt(listOfFiles.length)].getName();

                        boolean notInList = true;
                        for(int j = 0; j < numOfTrainingFiles; j++) {
                                if(temp == trainingData[j]) {
                                        notInList = false;
                                }
                        }
                        if(notInList) {
                                trainingData[countTrain] = temp;
                                countTrain++;
                        }
                }
                // make FULL list of  files
                while(countAll < allFiles) {
                        System.out.println("Making ALL file " + (countAll) +"\n");
                        String temp = listOfFiles[r.nextInt(listOfFiles.length)].getName();

                        allData[countAll] = temp;
                        countAll++;
                }
                // produce the data sets for the neural network
                makeDataSet(testData, dir, "test");
                makeDataSet(trainingData, dir, "train");
                makeDataSet(allData, dir, "alldata");

        // run the nn training
        NNetwork Network = new NNetwork();
        Network.trainNetwork();
    }

    public static void makeDataSet(String [] fileArray, String dir, String fileType)  throws IOException
{

                int limit;
                int numStats = 2;
                boolean makeFileStarted = false; // dont change this
                String currentFileName = "";
                String userClass = ""; // user classification of the data. Is captured from filename
                int count = 0;
```

```java
        int index = 0;
        int windowLength;
            int sampleSize = 1; // used to reduce the size of the input file (not used)

        for (int i = 0; i < fileArray.length; i++) {
                count++;
                currentFileName = fileArray[index];

                //  gets the correct character from the filename i.e. distractions
userClass = currentFileName.substring(1,2); // gets the SECOND character
// reduce the number of the cases here if required
// e.g      if(userClass.equals("2")) userClass = "1";

// convert sound file to bytes and read in file
ByteArrayOutputStream outp = new ByteArrayOutputStream();
    BufferedInputStream in = new BufferedInputStream(new FileInputStream(dir +
    currentFileName));

int read;
byte[] buff = new byte[1024];
while ((read = in.read(buff)) > 0)  {
  outp.write(buff, 0, read);
}

byte[] audioBytes = outp.toByteArray();
outp.flush();
in.close();

int nPoints = audioBytes.length;
double[] tempData = new double[nPoints]; // temporary file to hold

// make new data set (using sample size)
int next = 0;
for(int j=0; j < nPoints; j+=sampleSize ) {
    tempData[next] = audioBytes[j];
    next++;

    if(next >= nPoints) break;
}
// produce data set of correct length
  double [] ydata = new double[next-1];

  for(int j = 0; j < next-1; j++) {
          ydata[j] = tempData[j];
}
nPoints = ydata.length; // reset length if sampling has been used

// create number of windows that the file is to be split by
// this will be different depending on length of window
int numOfWindows = 60;// (int) Math.floor(nPoints / windowLength);
windowLength = nPoints / numOfWindows;

double[] tData = new double[numStats] ;
double[] wData = new double[nPoints / numOfWindows];
double[] concatArray;
double[] previousData = new double[100000];
int windowCount = 0;

System.out.print("Window length " + windowLength +"\n");
System.out.print("Number of Windows " + numOfWindows + "\n");
```

```java
        // create the spectrogram (FFT for each window)
int indexing = 0;
for(int k = 0; k < nPoints; k++) {
    // if window length reached create stats data for window
    if(indexing % windowLength == 0) {
            // create data for training
            Statistics stats = new Statistics(wData);

            tData[0] = stats.getMean();          // get the statistical data for the segment
            tData[1] = stats.getStdDev();

            // get previous window data and add new data
            if(windowCount > 0) {
                    concatArray = new double[tData.length + previousData.length];
                    System.arraycopy(tData, 0, concatArray, 0, tData.length);
                    System.arraycopy(previousData, 0, concatArray, tData.length,
                    previousData.length);
                    previousData = concatArray;
            }
            else // first window passes first set of data
                    previousData = tData;

            windowCount++;
            if(windowCount >= numOfWindows)
                                    break;

            indexing = 0;
    }
    wData[indexing] = ydata[k];
    indexing++;
}


// make the file (either Training or testing data set use with Weka nnetowrk classifier
try{
    new File(".\\Transform").mkdir();

    boolean makingIndividual = false;

    // making an individual file - perhaps for testing
    if(makingIndividual) {
            // for making an individual test file (not used)
    }
    else {
            // making a training set
            String fileName = "";
            if(fileType.equals("train")) fileName = "training.txt";
            else if (fileType.equals("test")) fileName = "testing.txt";
            else if (fileType.equals("alldata")) fileName = "alldata.txt";
            else fileName = "current.txt";

            // make the file header (just ran once at first iteration)
            if(makeFileStarted == false) {
                    // started to make the training file so list attributes
                        // making training file (contains multiple files)
                    PrintWriter writer = new PrintWriter(".\\Transform\\" + fileName, "UTF-
                    8");
                     writer.println("@relation Transform");
                     writer.println("");
```

```
                                    for(int l=0; l < limit; l++) { // counts in two so only uses real data
                                        writer.println("@attribute " + (l+1) + " numeric");
                                    }
                                    // the classes (can be reduced)
                                    writer.println("@attribute class {1, 2, 3, 4, 5}\n");
                                    writer.println("");
                                    writer.println("@data");
                                    writer.close();
                                    makeFileStarted = true;
                                }

                                // now add the individual data for each file processed
                                PrintWriter writer = new PrintWriter(new FileOutputStream(
                                    new File(".\\Transform\\" + fileName),
                                    true /* append = true */));

                                for(int k = 0; k < limit; k++){
                                    writer.format(Locale.UK, "%4.4f,", previousData[k]);

                                }
                                writer.write(userClass);
                                writer.println("");
                                writer.close();
                        }
                    } catch (Exception e) {
                        System.out.print("\nWriting file failed");
                    }
                    index++;
                }
    }
}
```

```
public class Statistics
{
    static double[] data;
    int size;

    public Statistics(double[] data) {
        this.data = data;
        size = data.length;
    }

    double getMean() {
        double sum = 0.0;
        for(double a : data)
            sum += a;
        return sum/size;
    }

    double getVariance()  {
        double mean = getMean();
        double temp = 0;
        for(double a :data)
            temp += (a-mean)*(a-mean);
        return temp/size;
    }
```

```java
    double getStdDev() {
        return Math.sqrt(getVariance());
    }

    double getMax() {
        double max = 0;
        for(double a :data)
          if( a > max) max = a;
        return max;
    }

    public static double median() {
        int middle = data.length/2;
        if (data.length%2 == 1) {
            return data[middle];
        }
        else {
            return (data[middle-1] + data[middle]) / 2.0;
        }
    }
}
```

```java
import java.io.FileReader; import java.util.Random; import weka.classifiers.Evaluation;
import weka.classifiers.functions.MultilayerPerceptron;
import weka.core.Debug; import weka.core.Instances; import weka.core.Utils;

public class NNetwork {
        public void trainNetwork(){
                try{
                        // read in the data
                        FileReader trainreader = new FileReader("............\training.txt");
                        FileReader testreader = new FileReader(".............\testing.txt");
                        FileReader allreader = new FileReader("...............\alldata.txt");

                        // create instances
                        Instances all = new Instances(allreader);
                        Instances train = new Instances(trainreader);
                        Instances test = new Instances(testreader);

                        train.setClassIndex(train.numAttributes() - 1);
                        test.setClassIndex(test.numAttributes() - 1);
                        all.setClassIndex(all.numAttributes() - 1);

                        // create and run classifier on training data
                        MultilayerPerceptron classifier = new MultilayerPerceptron();
                        classifier.setOptions(Utils.splitOptions("-L 0.2 -M 0.6 -N 500 -V 0 -S 9 -E 20 -H 3
                        "));
                        classifier.buildClassifier(train);

                        // save the results
                        Debug.saveToFile(".\\weka-neural-network", classifier);

                        // Evaluate the test file and pring results
                        Evaluation eval = new Evaluation(train);
                        eval.evaluateModel(classifier, test );
                        System.out.println(eval.toSummaryString("\nResults\n======\n", false));
```

```java
                    // produce cross validation using all the data and print results
                    Random rand = new Random(1);  // using seed = 1
                    int folds = 10;
                    eval.crossValidateModel(classifier, all, folds, rand);
                    System.out.println(eval.toMatrixString());

                    trainreader.close();
                    testreader.close();
                    allreader.close();

            } catch(Exception ex){
                    ex.printStackTrace();
            }
        }
}
```

Appendix O: Weka file format sample

A sample of accelerometer data that has been converted into Weka file format. The file consists of two sections:

- Section one demonstrates the attributes of data. In the example below there are 30 pieces of data within the file. The final attribute is the list of potential classes that the file can be assigned.
- Section two, which starts from the line @data, lists the 30 pieces of data, in this case the mean and the standard deviation for each of the 15 windows that the file has been split into. The final value i.e. 4 is the class that the data was classified as by the user when it was recorded on the device.

Note that this sample file contains a single dataset which could be used for testing the system for a single instance of data. Where the system is training or testing multiple files section two of the file would contain the details for all the appropriate data required for the specific task.

```
@relation Transform

@attribute 1 numeric
@attribute 2 numeric
@attribute 3 numeric
@attribute 4 numeric
@attribute 5 numeric
@attribute 6 numeric
@attribute 7 numeric
@attribute 8 numeric
@attribute 9 numeric
@attribute 10 numeric
@attribute 11 numeric
@attribute 12 numeric
@attribute 13 numeric
@attribute 14 numeric
@attribute 15 numeric
@attribute 16 numeric
@attribute 17 numeric
@attribute 18 numeric
@attribute 19 numeric
@attribute 20 numeric
@attribute 21 numeric
@attribute 22 numeric
@attribute 23 numeric
@attribute 24 numeric
@attribute 25 numeric
@attribute 26 numeric
@attribute 27 numeric
@attribute 28 numeric
@attribute 29 numeric
@attribute 30 numeric
@attribute class {1, 2, 3, 4, 5}

@data
8.8685,4.4055,1.7106,2.4655,0.4693,0.5070,0.6237,0.5898,0.8767,0.6681,1.0081,0.7375,0.8727,0.6377,0.6595,0.7421,0.3615,0.4494,0.5660,0.5807,0.6301,0.7479,1.8111,2.7569,3.7250,3.5362,1.2138,2.2041,1.2138,2.2041,4
```

Appendix P: Android implementation of Weka libraries

The full implantation of the Weka libraries utilise Java Swing components which are not compatible with Android implementation of Java classes / libraries. Therefore it is essential to utilise the stripped version of Weka which is available here https://github.com/shamtastic/Weka-Stripped

The same stripped version of Weka must be used for both the Java and Android applications otherwise there will be incompatibility issues when transferring classifier files to the Android implementation.

Three Android/Java classes are presented below:

1. DataSets – this class processes the data files to produce Weka compatible files. A test file is produced (i.e. from either a sound recording or accelerometer recording) and the NNetwork class is used to classify the file. The DataSets class uses the Statistics class to convert the raw data into features.

2. Statistics – this class is used to produce the mean and the standard deviation of a sample of data i.e. a window within the file

3. NNetwork – this class relies upon Weka algorithms to classify the test data produced on the device

```
package com.mhooper.sidisense.process;

import android.content.Context;
import android.util.Log;
import com.mhooper.sidisense.data.DataAccess;
import java.io.BufferedInputStream;
import java.io.BufferedReader;
import java.io.ByteArrayOutputStream;
import java.io.FileInputStream;
import java.io.IOException;
import java.io.InputStream;
import java.io.InputStreamReader;
import java.util.ArrayList;
import java.util.List;


public class DataSets {
    DataAccess data;
    static Context context;
    public DataSets(Context context) {
        this.context = context;
    }

    public static void makeActivityDataSet(String [] fileArray, String dir, String fileType) throws IOException {

        DataAccess data = new DataAccess();
        int numStats = 2;
        boolean makeFileStarted = false;
        String csvFileName = "";
        int index = 0;
        int sampleSize = 1; // not used

        for (int i = 0; i < fileArray.length; i++) {
            csvFileName  = fileArray[index];
            List<Double> accelBytes = new ArrayList<Double>();

            try {
                String line;
                FileInputStream fis = context.openFileInput(csvFileName);
                InputStreamReader isr = new InputStreamReader(fis, "UTF-8");
                BufferedReader br = new BufferedReader(isr);

                line = br.readLine(); // ignore header
                while ((line = br.readLine()) != null) {
                    String[] values = line.split(",");
                    for (@SuppressWarnings("unused") String str : values) {
                        double maxXY = Math.max(Double.parseDouble(values[0]), Double.parseDouble(values[1]));
                        double maxXYZ = Math.max(Double.parseDouble(values[2]), maxXY);
                        accelBytes.add(maxXYZ);
                    }
                }
                br.close();
            }
            catch(IOException e) {
                e.printStackTrace();
```

```
        }
        int nPoints = (int) Math.floor(accelBytes.size());
        double[] ydata = new double[accelBytes.size()];

        // make new data set (using sample size)
        int next = 0;
        for(int j=0; j < nPoints; j++ ) {
            ydata[j] = accelBytes.get(next);
            next+=sampleSize;
        }
        nPoints = ydata.length;

        int numOfWindows = 15;
        int windowLength;
        windowLength = nPoints / numOfWindows;
        double[] tData = new double[numStats] ;
        double[] wData = new double[nPoints / numOfWindows];
        double[] concatArray;
        double[] previousData = new double[100000];
        int windowCount = 0;

        // data for each window)
        int indexing = 0;
        for(int k = 0; k < nPoints; k++) {
            // if window length reached create stats data for window
            if(indexing % windowLength == 0) {

                // create data for training
                Statistics stats = new Statistics(wData);
                tData[0] = stats.getMean();         // get the statistical data for the segment
                tData[1] = stats.getStdDev();

                // get previous window data and add new data
                if(windowCount > 0) {
                    concatArray = new double[tData.length + previousData.length];
                    System.arraycopy(tData, 0, concatArray, 0, tData.length);
                    System.arraycopy(previousData, 0, concatArray, tData.length, previousData.length);
                    previousData = concatArray;
                }
                else // first window passes first set of data
                    previousData = tData;

                windowCount++;
                if(windowCount >= numOfWindows)
                    break;
                indexing = 0;
            }
            wData[indexing] = ydata[k];
            indexing++;
        }

        int length = previousData.length; // final array

        // make the file (either Training or testing data set use with Weka nnetowrk classifier
        try{
            // making a training set
            String fileContent = "";
            String fileName =  "accel_current.txt";

            // make the file header (just ran once at first iteration)
            if(makeFileStarted == false) {
                // started to make the training file so list attributes
                fileContent += ("@relation Transform");
                fileContent +=("\n");

                for(int l=0; l < length; l++) { // counts in two so only uses real data
                    fileContent +=("\n@attribute " + (l+1) + " numeric");
                }
                fileContent +=("\n@attribute class {1, 2}"); // the classes
                fileContent +=("\n");
                fileContent +=("\n@data\n");
                makeFileStarted = true;
            }

            for(int k = 0; k < length; k++){
```

```
                    fileContent += previousData[k];
                    fileContent += ",";
                }
            fileContent +=("?");

                // now save the file
                data.saveOnInternal(context, fileName, fileContent);

        } catch (Exception e) {
            e.printStackTrace();
        }
        index++;
    }
}
    public static void makeDistruptionsDataSet(String [] fileArray, String dir, String fileType) throws IOException {

        DataAccess data = new DataAccess();
        boolean makeTrainingFileStarted = false;
        String currentFileName = "";
        int numStats = 2;
        int count = 0;
        int index = 0;
        int sampleSize = 1; // used to reduce the size of the input file (not used)

        for (int i = 0; i < fileArray.length; i++) {
            count++;
            currentFileName = fileArray[index];

            // convert sound file to bytes and read in file
            ByteArrayOutputStream outp = new ByteArrayOutputStream();
            BufferedInputStream in = new BufferedInputStream(new FileInputStream(context.getFilesDir() + "/" + currentFileName));

            int read;
            byte[] buff = new byte[1024];
            while ((read = in.read(buff)) > 0) {
                outp.write(buff, 0, read);
            }

            byte[] audioBytes = outp.toByteArray();
            outp.flush();
            in.close();
            int nPoints = audioBytes.length;

            // create number of windows that the file is to be split
            int numOfWindows = 60;
            int windowLength;
            windowLength = nPoints / numOfWindows;

            double[] tData = new double[numStats] ;
            double[] wData = new double[nPoints / numOfWindows];
            double[] concatArray;
            double[] previousData = new double[100000];
            int windowCount = 0;

            // Get mean and SD for each window
            int indexing = 0;
            for(int k = 0; k < nPoints; k++) {
                if(indexing % windowLength == 0) {
                    // create data for training
                    Statistics stats = new Statistics(wData);
                    tData[0] = stats.getMean();        // get the statistical data for the segment
                    tData[1] = stats.getStdDev();

                    // get previous window data and add new data
                    if(windowCount > 0) {
                        concatArray = new double[tData.length + previousData.length];
                        System.arraycopy(tData, 0, concatArray, 0, tData.length);
                        System.arraycopy(previousData, 0, concatArray, tData.length, previousData.length);
                        previousData = concatArray;
                    }
                    else // first window passes first set of data
                        previousData = tData;

                    windowCount++;
                    if(windowCount >= numOfWindows) break;
```

```
              indexing = 0;
          }
          wData[indexing] = audioBytes[k];
          indexing++;
      }
      int length = previousData.length; // final array length

      // making an individual file - for testing
      try{
          String fileContent = "";
          String fileName = "disrupt_current.txt";

          // make the file header (just ran once at first iteration
          if(makeTrainingFileStarted == false) {
              // started to make the training file so list attributes
              fileContent += ("@relation Transform");
              fileContent +=("\n");

              for(int l=0; l < length; l++) { // counts in two so only uses real data
                  fileContent +=("\n@attribute " + (l+1) + " numeric");
              }
              fileContent +=("\n@attribute class {1, 3, 5}"); // the classes
              fileContent +=("\n");
              fileContent +=("\n@data\n");

              makeTrainingFileStarted = true;
          }
          for(int k = 0; k < length; k++){
              fileContent += previousData[k] + ",";
          }
          fileContent +=("?"); // we don't know the class
          // now save the file
          data.saveOnInternal(context, fileName, fileContent);
      } catch (Exception e) {
          Log.e("Files", "Disruption - writing file failed");
      }
      index++;
    }
  }
}
```

```
package com.mhooper.sidisense.process;

import android.content.Context;
import java.io.InputStream;
import java.io.ObjectInputStream;
import weka.classifiers.Classifier;
import weka.core.Instance;
import weka.core.Instances;
import weka.core.converters.ConverterUtils;


public class NNetwork {

  static Context context;
  public NNetwork(Context context) {
      this.context = context;
  }

  public String runNetworkFromFile(String type) {

      String classResult = "woops";
      String networkInRAW = type + "_weka_neural_network";

      try {
          ConverterUtils.DataSource source = new ConverterUtils.DataSource( context.openFileInput(type + "_current.txt"));
          Instances inst = source.getDataSet();
          inst.setClassIndex(inst.numAttributes() - 1);

          // Instance to classify
          int index = 0;;
          Instance toClassifyInstance = (Instance) inst.instance(index);//.copy();

          // Get the network file from raw
          InputStream ins = context.getResources().openRawResource(
```

```java
                context.getResources().getIdentifier(networkInRAW,
                    "raw", context.getPackageName())));

            // Deserialize model
            ObjectInputStream ois = new ObjectInputStream(ins);
            Classifier cls = (Classifier) ois.readObject();

            ois.close();
            ins.close();
            System.gc(); // Call garbage collection

            // PREDICTION
            double clsLabel = cls.classifyInstance(toClassifyInstance);
                classResult = inst.classAttribute().value((int) clsLabel);

            cls = null;
            inst.clear();

        } catch (Exception e) {
            e.printStackTrace();
        }
        return classResult;
    }
}
```

```java
package com.mhooper.sidisense.process;

public class Statistics
{
    static double[] data;
    int size;

    public Statistics(double[] data) {
        this.data = data;
        size = data.length;
    }

    public double getMean() {
        double sum = 0.0;
        for(double a : data)
            sum += a;
        return sum/size;
    }

    public double getVariance()  {
        double mean = getMean();
        double temp = 0;
        for(double a :data)
            temp += (a-mean)*(a-mean);
        return temp/size;
    }

    public double getStdDev() {
        return Math.sqrt(getVariance());
    }

    public double getMax() {
        double max = 0;
         for(double a :data)
            if( a > max) max = a;
        return max;
    }

    public static double median() {
        int middle = data.length/2;
        if (data.length%2 == 1) {
            return data[middle];
        }
        else {
            return (data[middle-1] + data[middle]) / 2.0;
        }
    }
}
```

Appendix Q: Experimental data cross-references (Available on accompanying CD)

Reference	Location on CD	File Names
Appendix Q-i	Experiment Cycles\Cycle_1\ Experiment_1	High effort vs low effort.xlsx High risk vs low risk Imagery vs detail.xlsx Optimistic vs fear.xlsx
Appendix Q-ii	Experiment Cycles\Cycle_1\ Experiment_2	Involvement Laptops.xlsx
Appendix Q-iii	Experiment Cycles\Cycle_2\ Experiment_1	Advert styles.xlsx
Appendix Q-iv	Experiment Cycles\Cycle_2\ Experiment_2	Purchase decision involvement.xlsx
Appendix Q-v	Experiment Cycles\Cycle_3\ Experiment_1	Imagery.xlsx Detail.xlsx
Appendix Q-vi	Experiment Cycles\Cycle_3\ Experiment_2	PDI results.xlsx
Appendix Q-vii	Experiment Cycles\Cycle_4	Final SIDI logic (system logic).xlsx
Appendix Q-viii	Experiment Cycles\Cycle_4	Final Logic Reviewed.xlsx
Appendix Q-ix	Experiment Cycles\Cycle_4	Final NEW Logic Review (PDI).xlsx
Appendix Q-x	Experiment Cycles\Cycle_4	aR1R2 Reviewed (EAB).xlsx

Appendix R: SiDISense application code (Available on accompanying CD)