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Recognising basic needs from mobile phone user behaviour to model the mobile user's emotional state

Master's Thesis

Espoo, May 3rd, 2010

Supervisor: Professor Mikko Sams

Instructor: Johan Himberg, Ph.D.

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ABSTRACT OF MASTER'S THESIS

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The mobile phone has grown out of its original scope while its importance for society has increased. From a simple communication tool, it has become not only a more elaborate communication platform, but also among other things a camera, a music player and an alarm clock. The user experience has drowned in a tsunami of features and it is only during the last 5 years the mobile phone manufacturers have realised it. The industry has lately been talking about a second wave — a wave of mobile ad campaigns.

Becoming aware of the mobile phone user's emotional state is an approach for mobile phone manufacturers to design for a better experience and for ad campaigns not to become the new Spam.

This thesis looks at this rather novel field, by clarifying what are the relevant theories of emotions, what computational model would be feasible and what data could be usable. Dörner's PSI model of emotions is examined and consequently the place of basic needs and personality as well. A small survey, while attempting to test part of the PSI theory, sheds light on some mobile phone emotional usage. Emotional changes are concluded as more accessible than the emotional states, due to the complexity of the theory of mind.

A future study collecting real data and in situ emotional reactions to the use cases from a large sample from a culturally narrow population would be of great help in evaluating what data has the most emotional content. Considerably more work will need to be done to determine if the PSI model is adequate for modelling in mobile phone context. From a privacy and ethics point of view, discussions need to be held on what data would be considered as acceptable to use even when anonymised.

Keywords: Mobile phone; emotion; basic needs; user behaviour; modelling

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Espoo, May 3rd, 2010

Christoffer Langenskiöld

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Abbreviations

BFI	Big Five Inventory, a test that measures the dimensions of the Five Factor Model
FFM	Five Factor Model, a comprehensive and empirical model of personality
MMS	Multimedia Messaging Service
nA #	Question number # relating to the need for Affiliation
nCE #	Question number # relating to the need for Certainty
nCO #	Question number # relating to the need for Competence
NAQ	Need Assessment Questionnaire, a test to measure the current level of need
OCC	Ortony, Clore and Collins' model of appraisal and emotions
PSI	Principal of Synthetic Intelligence, the theoretical framework describing human psychology
rho	17th letter of the Greek alphabet
SMS	Short Message Service

1. Introduction

Mobile phones are slowly replacing more and more portable objects that we have been carrying and are still carrying with us: pictures in the wallet, address book, calendar, music player, common transportation tickets and even our wallet. What's next to come? Keys? Digital ID? There are two main reasons why our mobile phone is getting such an essential place in our life: primarily it enables a new level of communication and secondarily multi-functionality (e.g. watching pictures, movies, playing music, games or browsing the Internet). Throughout the day, emotions are expressed through many modalities (e.g. speech, facial expression), but also in our behavioural and product usage (e.g. social interaction, application usage, movement). Most people sleep with their mobile phone placed on their beside table and take it nearly everywhere they go, which makes the mobile phone the ideal source of behavioural and sociological data. A way one can use that type of data is for modelling the user's emotional states. There is an explosion happening in contextual and social networking mobile applications, some existing applications that take such contextual data in use are (See Appendix C for a more extensive list): ContextWatcher[1] is a mobile phone application, which allows the user to associate her/his experiences with Bluetooth devices. Panasonic VS3[2] is a mobile phone, which has a LED light blinking with various colours, in function of the emoticons received in SMS messages. Jaiku[3] is a mobile social application, which shares the user's context (the number of Bluetooth devices around, whether he/she last used her/his phone, calendar entry, location, presence line and ringing profile) with her/his friends. Feel*Talk[4] is a feature of a NTT-DoCoMo-Panasonic mobile phone series, which uses voice analysis to recognise the user's mood. This is used for tagging conversations. This handset can express the mood of a conversation in 45 different types of animation, illumination and soundscape after the call, and retains it as icons on your Call History and Call Memory. Other variables were taken into account like length of the call, time of the day and the phase of the moon.

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[1] ContextWatch: http://contextwatcher.web-log.nl/

[2] Panasonic VS3: http://www.mobile-review.com/review/panasonic-vs3-1-en.shtml

[3] Jaiku: http://www.jaiku.com

[4] Feel*Talk: http://panasonic.jp/mobile/p702id/feel_talk/index.html

1.1. Motivation

As phones have gained features over the years, the user experience has become awfully complex and stressful. Design and software architecture decisions need to be made as the phone are being designed. Do the target users need all these features to have the best experience? The mobile phone user's emotional state could allow mobile phone manufacturers to filter features to keep the target user of a specific phone at the optimal user experience level.

Another field, which could benefit of such insight, is mobile marketing. Mobile marketing has been very slow at taking off, for the main reason that people do not want a new Spam channel. That not only could allow the mobile phone to self-learn what type of ads would suit you, but also to act as a local filter allowing only certain campaigns to come through. For example, emotionally sensitive ad campaigns could be delivered to people in the right emotional state, or two different ads could be designed for positive and negative emotional states. See Appendix A for a more details and fields where this could be applied.

1.2. Objective

The goal of the thesis is exploring how much the recognition of emotions from mobile users has been researched, and therefore define the novelty of the topic to set our expectations.

The main objective of this study can therefore be described as:

> A literature study on this rather novel field and the creation of guidelines for the selection of data.

1.3. Research question

In order to answer the main research question, the following focused questions will be answered in the course of the study, keeping the mobile phone user in mind:

- What are emotional states?
- How are emotional states recognised?
- How are emotional states modelled?
- What type of mobile phone data would best suit the modelling of emotional states?
- How well does it perform using the most appropriate model of emotion?
- Would a computational model of emotions be feasible in the context of mobile phone?

The research question of this thesis can be summarised as follows:

What mobile phone user behaviour could be used to model emotional states?

1.4. Structure of the thesis

The thesis is structured according to the plan below:

- Chapter 1 **Introduction**
- Chapter 2 **Background** gives a generic framework on the thesis's topic and a detailed description of relevant theories and classifications of emotions, current methods to recognise emotions and different models of emotions.
- Chapter 3 **Survey**, the personality test and the need assessment questionnaire are described and results analysed to see whether mobile user data has any correlation with emotions.
- Chapter 4 **Discussion** is a presentation and discussion the results of the study, where we argue how feasible it is to use mobile user data to model emotional states.
- Chapter 5 **Conclusion** presents the outcome of the study, describes directions for future research.

2. Background

There are many definitions and theories of emotions, and several ways to recognise and model emotions. Let us look into these to see how this relate to mobile phone user behaviour. Emotional state is a term chosen in this thesis to refer to a simplified model of emotions, which has a valence (e.g. It can be positive or negative), an intensity and can last from hours to weeks.

A literature study was conducted on through publications from years 2000-2007 of *Personal and Ubiquitous Computing* and other publications found on Google Scholar. Most of the interesting papers were the result of a snow ball research from main literature, due to the scarce papers on the matter. How influential a publication was also taken into account, using the number of referencing works Google Scholar gives. Sources for this literature were (a) searches on electronic databases like Google Scholar and Science Direct, using as main keywords emotion, mood, affect, recognition, model and mobile phone; (b) manual searches of the reference lists of all works found through process (a); and (c) a manual search of Cognitive Science, Psychology and Human-Computer Interaction texts in the libraries of several Helsinki universities.

Although this literature study was extensive and thorough, the topic is so novel and cross-disciplinary that terms still vary it is likely the literature analysis in this thesis doesn't cover the entire body of published works. The types of publications included genres such as Psychology, Artificial Intelligence & Robotics and Human Computer Interaction. The selection of works were considerably influenced by the relevance of the paper and the amount of references it had been assigned in Google Scholar.

2.1. Emotional state

The term *emotion* has been used scientifically both in narrow and broad senses. When used in a narrow sense, it has been referring to short, intense emotions. When used in a broader sense, it includes these seconds long emotions, but also longer emotional-related states, that can stretch over months. Thus we need to define what type of emotions we are interested in.

2.1.1. Classification

Emotions, once called by Cowie & Schroeder (2005, p.306) *pervasive emotions*, are emotional states that will last between hours and months. Let us call them *emotional states*. What we call an emotional state is described by Oatley et al. (2006) as full-blown emotions and moods: affective phenomena (see Figure 1), which last between hours and months.

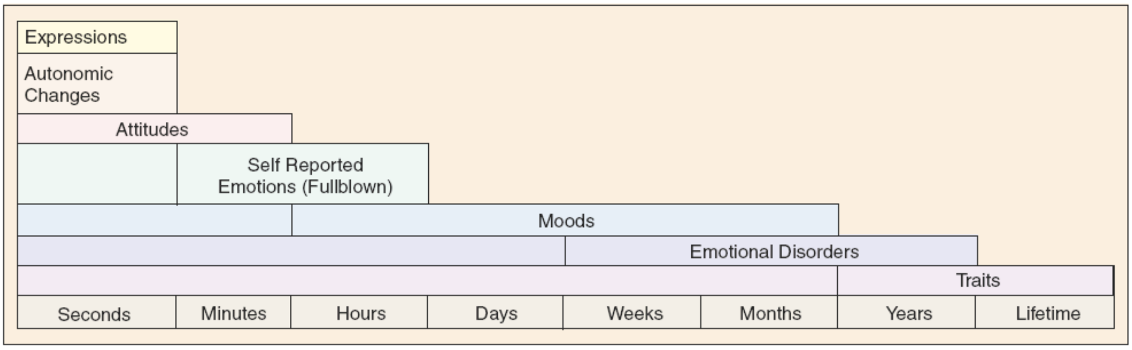

Figure 1. A spectrum of affective phenomena in terms of the time course of each (from Oatley et al., 2006)

A full-blown emotion is the externalised version of an emotion, a natural instinctive state of mind, which derives from social and cultural factors (Ekman, 1984), motivational states (Ortony et al.,1988) or at a lower level basic needs (Cosmides & Tooby, 2000) and personality traits (Romano & Wong, 2004). It also falls under the category of *emergent emotion* (Douglas-Cowie, E., et al., 2006), which also includes externalised and suppressed emotions.

A mood is a state of mind, which *colours* the person's general outlook with a certain feeling. As time passes by, the person tends to forget the reason why s/he experiences the emotion. Beedie et. al. (2005) distinguish between mood and emotion, and some of the differences are: largely cognitive/behavioural consequences, not displayed/displayed, mild/intense, no distinct physiological patterning/distinct physiological patterning, stable/volatile, rises and dissipates slowly/rapidly. These differences clarifies the interface between the emotion and the mood, and does support the concept of mood is an emotional state which has lasted for a longer time period (hours, days or weeks) (Oatley, 2006). We consequently don’t a different approach to model the mood. According to Rousseau and Hayes-Roth (Rousseau & Hayes-Roth, 1997), two categories can be distinguished: self-directed and agent-directed moods. As they can be attached to objects and places, it creates the possibility for moods to co-exist through space and time, i.e. in different contexts. We take advantage of the fuzzy line between moods and full blown emotions to put them under one term: *emotional state*. There has been several attempts at the classification of emotions (Kemper,1987; Scherer 2005; Thamm 2006), but there is no consensus over these classifications other than the primary emotions.

2.1.2. Theories

A short overview of theories of emotions are presented below based on the more detailed description made by Marsella et. al. (2010), to which the hybrid theory was added.

- *Appraisal theory*: In this theory, also the most popular theory among psychological perspectives on emotions, emotion is argued to depend on how people appraise and evaluate the events around them based on their believes, desires and intentions. Frijda (1993) and Lazarus (1991) clearly see emotions as dependant on the relationship with the stimuli and the goal, which would require deep exploratory research.

- *Dimensional theory*: As the name describes it, this theory argues that emotions should be conceptualized as points in a continuous dimensional space, using dimensional models with for example self-report verbal scales (Mehrabian & Russell, 1974; Watson et. al., 1988), visual self-report scales (Kunin, 1955) or physiological measures (Vrana et. al., 1986; Lanzetta & Orr, 1986; Ravaja et. al., 2004). Dimensional theorists believe in a core affect which blurs the line between mood, emotion and affect, which is consequently not object-oriented. These dimensions tend to decays over time to some resting state, influenced by tendencies like personality traits (Marsella et. al., 2010). Considering that this theory describes all behaviours in terms of dimensions, and the evidences (Barrett, 2006) that dimensional theories are better at recognising human emotional behaviour than the ones that rely on discrete labels, this theory would be appropriate for this thesis.

- *Anatomical theory*: Anatomic theories try to mimic the neural circuitry that underlies the emotional process (LeDoux 2000), some being fast (or automatic) and some being slow (relying on a higher-level of reasoning processes). Behaviour can well be tracked on mobile phones and the length of sequence of actions could therefore be representing the length of the process, which makes this model a potential candidate for the analysis of mobile phone usage in term of the sequences of actions.

- *Rational theory:* Rational approaches abstract emotional functions in humans to use them in artificial intelligence (Sloman, 1987). This theory would be more appropriate for a human-computer interaction situation, since the place of emotion in this theory is more as a goal, but not quite in this context as the user's emotion isn't the known.
- *Communicative theory*: "Communicative theories of emotion argue that emotion processes function as a communicative system; both as a mechanism for informing other individuals of one's mental state – and thereby facilitate social coordination – and as a mechanism for requesting/demanding changes in the behavior of others – as in threat displays (Keltner and Haidt 1999; Parkinson 2009)." This theory wouldn't be used for the same reasons as the rational theory, it isn't the embellishment of human-computer interaction we are after.
- *Hybrid theory*: Hybrid theories are a mixture of other theories (Bach, 2009; Peter & Herbon, 2006). Three successes of the PSI theory (Bach, 2009) have been found in replicating human behaviors of complex tasks, for example that crowding alters cognition, emotion and motivation (Dörner et. al., 2006). The approach of mixing theories could be interesting considering the wide variety of data type in the mobile phone.

This leaves us with the dimensional theory, the anatomical theory and hybrid theory as potential theories.

2.1.3. Dimensions

The number of dimensions can vary from a unique dimension (usually valence) to a more complex space like Dörner's model of emotion (Bach, 2009), which is made of 6 dimensions (arousal, resolution level, goal directiveness, selection threshold, xsecuring behaviour and valence). But considering emotional states are the scope of the thesis, both emotions and moods should be considered. In order to leave flexibility in the choice of data, a two-dimensional space is chosen (see Figure 2): valence and arousal.

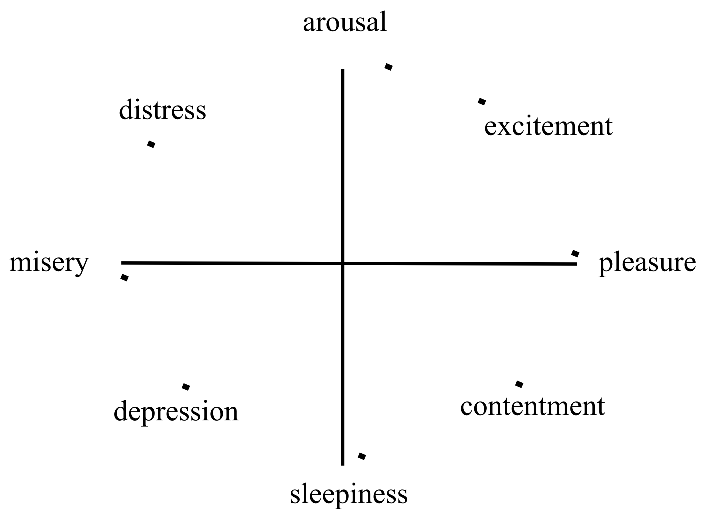

Figure 2. Russell's eight affect concept (from Russel, 1980)
These affects are placed using the pleasure and arousal dimensions.

2.1.4. Recognition

Recognising emotions requires knowledge of the link between emotions and actions, and the expression of emotions.

Emotions and actions

Already in 384-322 BCE were emotion and behaviour related by Aristotle by a systematic analysis of emotions, connecting emotions to actions (Elster, 1999). Frijda and Mesquita define emotions as "modes of relating to the environment: states of readiness for engaging, or not engaging, in interaction with that environment" (Oatley et. al., 2006, p.28). The translation of "action" and "interaction with the environment" is, in this context, behaviour, which has, in most cases, a sociological and communication context. It is only recently the non-social aspect of behaviour, such as the label user behaviour, has received more attention (Oatley et. al., 2006). By user is meant the user of a product (or service), ranging from a toothbrush, a mobile phone, to a website. Emotional states of such user are what we are after and are still expressed through a few defined channels (facial expressions, voice, written text, and physiological signals) and reflect unconsciously through other behaviour patterns, the question is which behaviour. A clarification of the modalities (or channels) people use to express emotions is needed before we can look into how they are recognised.

Expression of emotions

Emotions are expressed through different channels both intentionally or unintentionally. In order to clarify these we categorised them into 6 groups, since the categories that have been encountered during the thesis were missing some modalities, mostly due to their overlapping and level of complexity. Figure 3 is based on Lisetti's classification (C Lisetti et. al., 2003) and includes the majoritiy of the modalities.

Kinesthetic arousal	Acoustic expression	Body language
blood pressure	average pitch	facial expression
skin galvanic resistance	intensity colour	gesture
pupil	speaking rate	posture
brain wave	voice quality	proximity
heart rate	articulation	
	non-speech sound	

Kinesthetic expression	Product usage	Mental expression
touch	frequency	linguistic
pressure	quantity	music
	entropy	art
	use cases	

Figure 3. Classification of emotion expression modalities

Lisetti's categories are user-centric, but are never-the-less contextual-dependent, as these are limited to main human computer interaction media. These categories presented in this thesis try to be mobile-user-centric, implying the context is more versatile. The structure in which they are arranged are by level of complexity. For example the difference in speech can be distinguished by acoustic features like intensity, tone and pattern, as well as mental expression features like word counts, metaphors, other figure of styles or colours used to communicate emotions.

Recognition from traditional modalities

Voice and facial expression are the main modalities for humans to express their emotions and according to Ekman & Friesen (1975) there are universally recognised facial expressions for the basic emotions, and for that reason the most widely used modalities to recognise emotions. Facial recognition has already been integrated in main stream technology, like Sony's compact digital cameras[5], which detects the optimal smile to take the picture. Emotion recognition from voice has been used in the context of mobile phone (the co-operation between NTT-Docomo and Panasonic), but requires such processing power that it couldn't be contained inside a mobile phone, so we discard that option, as for video conferencing. The second most common type of modality is physiological signals, such as heart rate (Vrana et. al., 1986), skin galvanic response (Lanzetta & Orr, 1986), Facial electromyography and eyes (Ravaja et. al., 2004) and fMRI (Büchel et al, 1998). More details on these methods are listed in the Appendix E. Unfortunately sensors measuring kinaesthetic arousal such as heart rate or blood pressure, which can be connected over bluetooth, are not yet common practice.

Recognition from product usage

Some sensors have managed to become a standard part of several high-end mobile phones (e.g. GPS, cameras, light sensor, touch screens, microphones, bluetooth and accelerometer), which has already been tapped into by many location sensitive mobile applications. Apparently out of the ordinary locations play a more important socio-emotional role than everyday locations, where people and relationships take over that importance (Arminen, 2006). This shows us how context sensitive emotional content is, and that in order to make a solid model, different data types should be used in the model.

Currently, only text analysis (Shaikh, 2009; Neviarouskaya 2007, 2009) and input speed and frequency (Ball et. al. 1999, Klein et. al. 2002, Balomenos et. al. 2004) seem to have been used for emotion recognition in the category of product usage. Text analysis shall be discarded for privacy concerns, and input patterns as it would only work with an application located on the device.

A new approach seems to be needed considering the data we are looking at since none of the types above are available without breaching on privacy by looking at the content of the data. In the use case where such an application would be running else where than on the user's mobile phone, e.g. on the mobile operator's database, it is important to keep the privacy issue as a high priority. Before such recognition becomes plausible, a model emotional needs to be in place.

[5] The Sony DSC-T70 and DSC-T200 Cyber-shot cameras recognise the best smiles for a picture.
See http://www.reuters.com/article/idUSGOR44589420070914

Artificial Intelligence models used for virtual agents are rather simplified version of the theories, but are the place where to start. The type of data which we would be looking at were listed by Verkasalo (see Appendix F), e.g. Clock/Alarm, Inbound voice call, Outbound SMS message. This data can be interpreted in a controlled settings, but in reality context varies a lot, making it quite a lot more complicated. Possibly, context should therefore not be neglected as it gives experience meaning (Guarriello, 2006). Ways emotions have been collected from mobile users until today has been occasionally using voice recognition (the co-operation between NTT-Docomo and Panasonic) or using most commonly direct feedback on the device, either when the user feels like it or automatically prompted by the application such as SocioXensor (more details on tools to collect both subjective and objective data from mobile phones in Appendix C).

Using data mining we could spot specific activities during the day, which according to Kahneman & Krueger (2006) would reflect a specific level of subjective well-being, i.e. an activity where people are happiest. Based on common sense, those are linked to certain mobile data types in the list that follows.

Very positive

- intimate relations: phone muted + time
- socialising after work: location + time + phone activity + social network
- relaxing: location + time + phone activity
- eating: time + location + phone activity
- watching TV: MTV duration + location + time
- exercising: time + phone activity duration

Neutral positive

- housework: time + location
- shopping: time + location + purchases
- napping: time + location + phone activity
- cooking: time + location
- computer non-work: time + location + 3rd party

Less positive

- childcare: time + location

- evening commute: time + location
- working: time + location
- morning commute: time + location

2.1.5.Models

A model of emotions is a simplified description of a theory of emotions, i.e. what emotions are and where they come from, which is commonly described as valanced reactions that result from subjective appraisals of events. Artificial Intelligence and neuroscience have been the main areas, where emotion modelling has taken place. The PSI model and the eCircus were added to Marsella and Gratch's history of computational models of emotion (see Figure 4). We will not go further into each models, but an extensive description can be found in Marsella et. al., 2010).

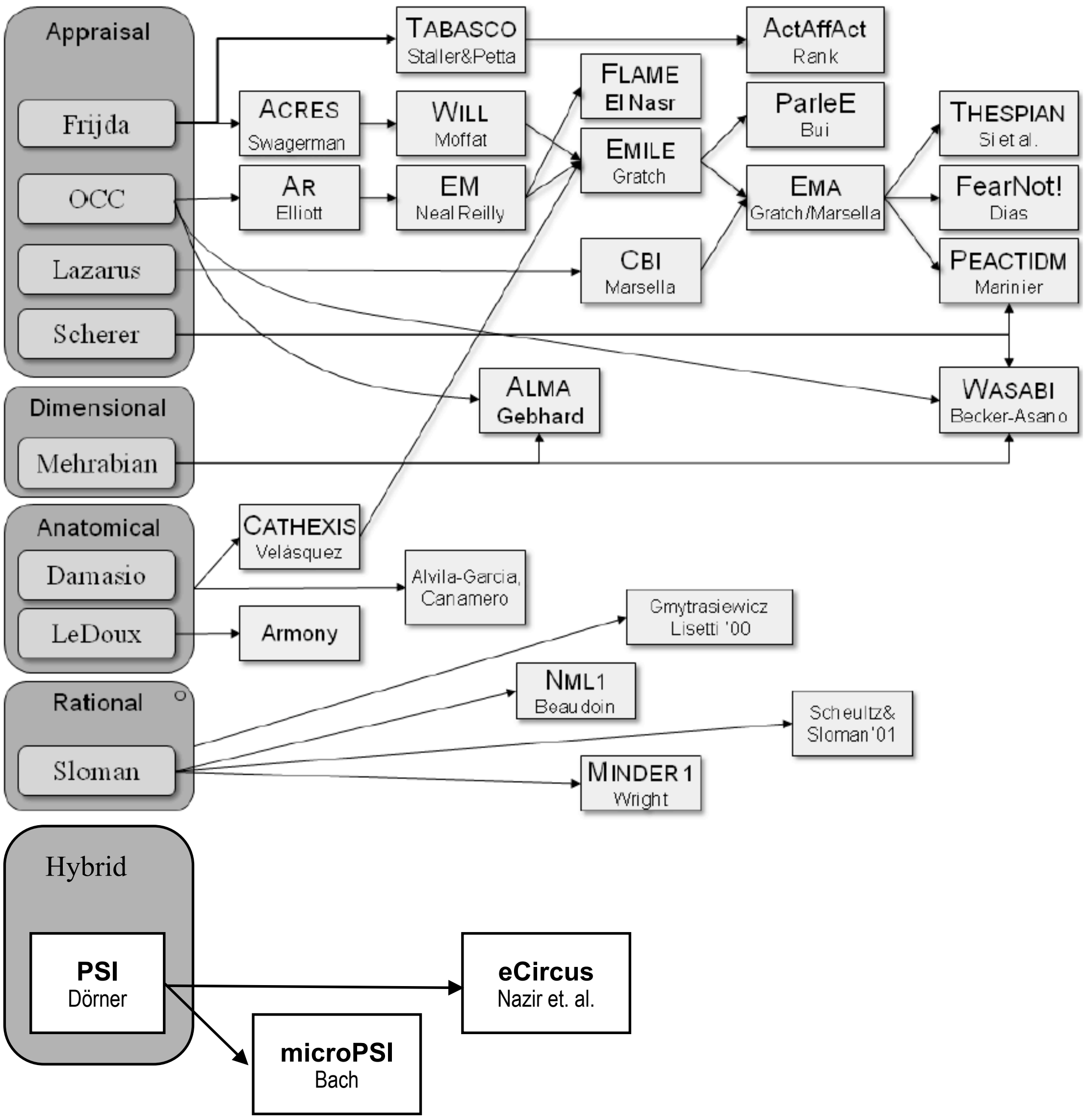

Figure 4. A history of computational models of emotion (adapted from Marsella et. al., 2010)

Marsella describes models as based on 4 different perspectives of emotion (Appraisal theory, Dimensional theory, Anatomical theory or Rational theory), which are explained in Section 2.1.2. An interesting model, the Dörner's PSI model (2001), was added under the new category called *hybrid theory* of emotion (the term *hybrid* that was used to describe the PSI model in (Schaub, 2001)), due to its theoretical assumptions based on appraisal theory's intention without being based on an appraisal system, the dimensional theory's concept of dimensions, decay and dispositional tendencies (such as personality traits) and the anatomical theory's "neuronal sub-symbolic processes (which run the perception and memory tasks)"(Schaub, 2001, p.339).

Bach (2009) provides the first thorough translation and insights into Dörner's PSI theory, which had only been in German until then, probably a reason why it has remained relatively unknown. He describes emotions, from Dörner's (2001) more psychological point of view, as emerging from the system through modulation of the cognitive processes, which depends strongly on basic needs and the deriving intention. Considering at the large amount of models that were built based on Ortony, Clore and Collins' model (OCC), it would feel natural to use the OCC, but an interesting issue in PSI is that emotions are not the product of a reaction but the state of the needs, how easily they will be fulfilled, memory and the incorporation of personality as thresholds, which contributes to the conception of more realistic architecture (Bach, 2009).

PSI theory is a model of emotion, personality and action, that attempts to link the body and mind of virtual agents and is driven by the need to fulfil basic needs, including originally existence preserving need (sleep, food, exercise), species-preserving need (sexuality), affiliation need (need to belong to a group and engage in social interactions), certainty need (predictability of events and consequences) and competence need (capability of mastering problems and tasks, including satisfying one's needs), but considering it tends to be in a survival context, it has more weight on physiological needs of existence preservation. Considering today mobile devices are essentially a communication device, we will put more weight on the need for affiliation. As noticed from the illustration of the model (see Figure 5), PSI's main variables are (a) memory of past locations and associated events (i.e. mobile phone calls, SMS, the quality of the operator signal or the general usage of the mobile phone), (b) present location and events, (c) personality determining to the selection threshold and (d) the state and change of needs as time passes.

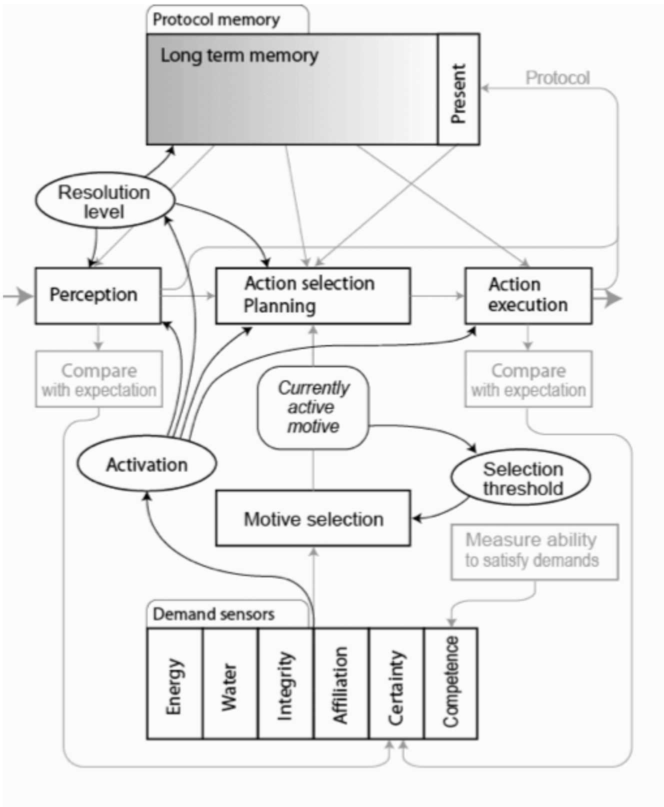

Figure 5. PSI model (from Bach, 2008)

Needs, the success probability and the urgency make the intention in the Dörner's model. The needs are self-depleting and a set selection threshold defined by the personality traits define the urge to fulfil a specific need. Additionally, how well an action is planned, i.e. the resolution level will be one of the emotional state's parameters. The action selection is then influenced by the resulting motivation and memories relative to related past situations and the perception of the current situation and the success probability. Practically, emotions reflect through these parameters. For instance as described by Aylett, anger is characterised by intentions not able to be executed, very high need for certainty, high arousal, high selection threshold and low resolution level; joy by intentions (surprisingly) not able to be executed due to minor obstacles, low need for certainty, medium arousal, medium to high selection threshold and medium to high resolution level; anxiety by intentions persistently not able to be executed, very high need for certainty, high arousal, low selection threshold and low resolution level. Dörner's model is driven by needs, we therefore need to look into what needs could be reflected in mobile user data.

2.2. Basic needs

Most models that include needs are based on Maslow's Hierarchy of needs. Dörner's needs make no exception as the needs of the cognitive architecture Clarion (Sun, 2006) it is constructed upon are themselves based on Maslow's Hierarchy of needs. Clarion's needs are labelled primary innate drives (water, food, danger avoidance) and secondary drives (belongingness, esteem and self-actualisation), which is a simplified version of Maslow's basic needs. Maslow's Hierarchy of needs is a very respected theory where the human thrives to achieve goals defined by five basic needs, which are physiological, safety, belonging, esteem and self-actualisation. They are arranged in a hierarchical structure (see Figure 6), where the lower need always needs to be relatively satisfied to allow the next need to get importance for the person (Maslow, 1946).

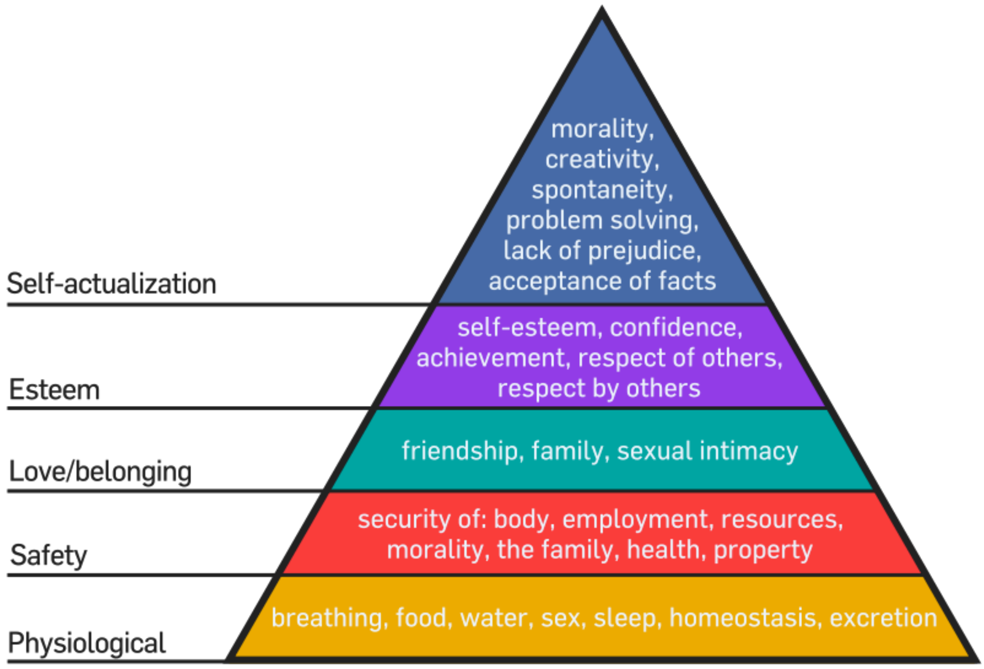

Figure 6. Maslow's Hierarchy of needs (Diagram by Factoryjoe [6])

Dörner's goal being the PSI agent, he has reduced the agent's needs to preserving need (water and food), affiliation need (need to belong to a group and engage in social interactions), certainty need (predictability of events and consequences) and competence need (capability of

[6] Diagram by Factory licensed under Creative Commons Attribution-Share Alike 3.0 Unported. http://en.wikipedia.org/wiki/File:Maslow%27s_Hierarchy_of_Needs.svg

mastering problems and tasks, including satisfying one's needs) to fit the context. Mobile phone usage is a human behaviour and should therefore also reflect basic needs. Here's how.

1. *Physiological needs*: Governed by the principal of homeostasis, the physiological needs are vital to survive. Maslow believed that when a person is deprived from all of them, the higher needs will become insignificant. These needs consists of air, water, food, sleep, warmth and sex. Sleeping patterns can easily be recognised by logging the first and the last phone activity in the day, to which accuracy could be increased if the mobile phone's accelerometer would be taken into use.

2. *Safety needs***:** include personality security, financial security, health, well-being, safety net against accidents/illness and the need for certainty. This need when unfulfilled triggers feelings of loneliness and alienation. Having a mobile subscription would reflect having a shelter, as operators tend to require subscribers to have a fixed address. The stability and the level of total monthly duration of phone calls made would reflect financial security, as minutes cost. For someone having a stable monthly fee above a certain amount would reflect a certain level of financial security. The level for certainty could be reflected in the reliability of the user's phone and the mobile operator's network, but is dependent on the Geert Hofstede's uncertainty avoidance cultural dimension [7].

3. *Social needs* is the most important level in the Maslow's hierarchy, with regard to this thesis, as it is about emotionally-based relationships in general, such as friendship, intimacy, having a supportive and communicative family. In absence of love, belonging and acceptance, many people become susceptible to loneliness, social anxiety and depression. Depending on the strength of the peer pressure these can be stronger than safety and physiological needs. The level can be expressed in the belonging to clubs, religious groups, sports teams, gangs or small social connections. Frustrated needs makes the person feel inferior, weak, helpless and worthless. The size and the strength of the links in the user's community, i.e. the need for affiliation, can be found by analysing phone calls and text messages using social network analysis.

4. *Esteem needs* includes respect, recognition, self-esteem, self-respect and respecting others. This is strongly culture-related and follows specific rules. Hanging up on an incoming call or not returning calls or text messages could reflect disrespect depending on the level of the

[7] Geert Hofstede's cultural dimensions are summarised at http://cl.rikkyo.ac.jp/zenkari/2009/2009/05/13/Geert_Hofstede.doc

Geert Hofstede's individualism cultural dimension.

5. *Self-actualisation*: After all the previous needs are fulfilled, comes a need to make most of one's abilities. Maslow says "A musician must make music, an artist must paint, a poet must write, if he is to be ultimately happy. What a man can be, he must be." (Maslow, 1943, p. 382). If unaccomplished, the person usually feels on edge, tense, lacking something, restless. Dörner translated this need to the need for competence. The need for technological competence could be measured by collecting the diversity of activities on the mobile phone and how advanced are the features the user is using.

The needs that seem to be recognisable from mobile phone data could therefore be sleep, financial safety, shelter, certainty, affiliation, respect and respecting others, and technological competence. We could therefore categorise those needs with Dörner's labels; respectively: existence preserving needs (sleep, financial safety and shelter), none would fall in species preserving needs, need for certainty, need for affiliation (affiliation, respect and respecting others) and need for competence (technological competence).

One big issue with the recognition of needs is the resolution which the data point is associated to in the big picture. This would be research of its own, so it is put aside in this thesis.

Since "there is no one 'correct' way to do a need assessment" (Kaufman, 1979, p.207), we take the approach of finding mobile phone events which are related to needs using common sense. That questionnaire shall be called the Need Assessment Questionnaire, so in order to map certain behaviours to actions meant to behaviour the needs, we conduct a survey which attempts to link behaviour, personality and changes in emotional states.

2.3. Personality traits

Personality has been combined to many models of emotions (Dörner 2001; Egges 2003; Zhou 2003), which has not only lead to increased accuracy, but has also received a more positive peer attention for being a feasible theory. As mentioned above, Dörner uses personality traits as *selection thresholds for needs*.

From a general point of view, personality traits are influenced and shaped by individual learning and experiences, and interaction between culture and that individual resulting in beliefs, expectations, values, desires and behaviours (Watson, 2000; McCrae et al., 2000). Caspi et al.

(2003) support that a 3 years-old child's behaviour can already depict personality traits of a 26 years-old person, and Soldz & Vaillant (1999) that it is carried along at least 40 years of your life. The majority of mobile user should therefore have relatively stable personality traits. Never-the-less changes in personality may occur with diet, medication, significant events or learning. Some research has been done on personality in the context of mobile behaviour (Bianchi & Phillips), which I haven't found about emotions and basic needs. Raad et. al. (1998) report coefficients of equivalence of the Big five traits across cultures (ranging from 0.23 to 0.85), which according to Triandis & Suh (2002) leaves us with four consistent traits across cultures.

When personality is studied and measured in relation to pattern of behaviour, thought and emotion, it is referred to as trait theory. It is based on the theory that personality is made of measurable traits, which are relatively stable over time, differ between persons and influence behaviour. There are two main taxonomies, which differ in the number of traits: (a) Eysenck's three-factor model, which includes the traits of extraversion, neuroticism, and psychoticism, and (b) Goldberg's Five Factor Model (FFM) of personality traits (extraversion, agreeableness, conscientiousness, neuroticism and openness to experience). FFM has clearly taken over Eysenck and Cattell's influence on the scientific community over the past 10 years as by 2006 over 300 publications per year had referred to the FFM compared to less than 50 to Cattell (the pioneer of personality traits) or Eysenck's theories (John et. al., 2008). The key factors are described below (John, 2008).

1. *Extraversion*. This dimension describes whether a person is talkative, assertive, active, energetic, outgoing, outspoken, dominant, forceful, enthusiastic, show-off and sociable or quiet, reserved, shy, silent, withdrawn, retiring.

2. *Agreeableness*. This dimension describes whether a person is sympathetic, kind, appreciative, affectionate, soft-hearted, warm and generous or fault-finding, cold, unfriendly, quarrelsome and hard-hearted.

3. *Conscientiousness*. This dimension describes whether a person is organised, thorough, playful, efficient, responsible and reliable or careless, disorderly, frivolous, irresponsible and slipshot.

4. *Neuroticism*. This dimension describes whether a person is tense, anxious, nervous, moody, worrying, touchy and fearful or stable, calm and contented.

5. *Openness to experience*. This dimension describes whether a person has wide interests, is imaginative, intelligent, original, insightful, curious, sophisticated and artistic or has narrow interests, is commonplace, simple, shallow and unintelligent.

The classic way these personality traits has been obtained has been through factor analyses to various lists of traits adjectives applied in personality test questionnaires based on the Lexical Hypothesis (Allport & Goldberg, 1936). The big five personality traits have become a standard in psychology, and has consequently been recognised using automatic text recognition (Mairesse, 2007; Argamon, Dhawle, Koppel, & Pennebaker, 2005; Mairesse & Walker, 2006a, 2006b; Oberlander & Nowson, 2006) social network structure analyses (Kalish & Robins, 2006; Stokes, 1985), mobile phone usage analyses (Bianchi & Phillips, 2001; Butt & Phillips, 2008; Phillips et al., 2006; Pöschl & Döring, 2007) or Internet usage (Amichai-Hamburger, 2005; Landers & Lounsbury, 2006; I. Lee, Kim, & Kim, 2005). Shortly, text analysis was used by Mairesse, Walker, Mehl, & Moore (2007) in a study on automatic recognition of all five personality traits from text corpus and conversation (see Mairesse and his colleagues work for well list of features, rules and relative errors). Mairesse (2007) programmed as result an open-source Java application[8] to recognise personality traits from essays, chat logs, e-mails, thoughts or other sources, which would allow an implementation of a mobile version quite speedy. Consequently Mairesse's text analysis could be used to recognised personality from emails and text messages, but breeches privacy concerns by analysing relatively private textual content. Using several of these methods a consolidated recognition of personality traits could be attained (see Figure 7).

[8] Mairesse's personality recognition Java application: http://mi.eng.cam.ac.uk/~farm2/personality/demo.html

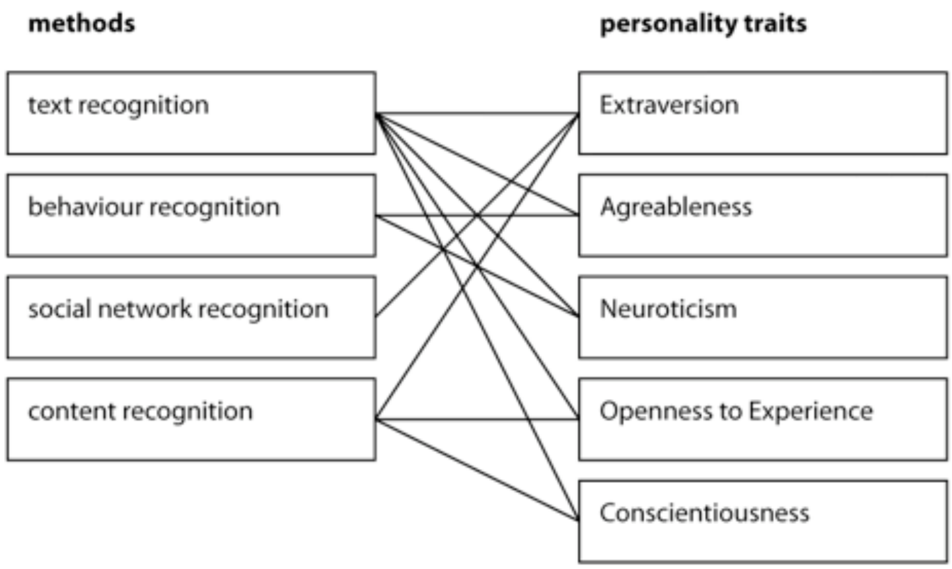

Figure 7. Recognising personality traits using several recognition methods

According to table 1 and 2, each method seems to perform better at recognising a specific personality trait; combining several methods would therefore be a good way to get an accurate recognition of all the personality traits.

Practically, all five traits could be recognised using Mairesse's text recognition model and behaviour analysis. Extraversion and Neuroticism traits could be recognised by measuring the size of one's social network. Extraverts have larger numbers of social support alters (e.g., Bolger and Eckenrode, 1991; Furukawa et al., 1998; Henderson, 1977) who tend to be more diverse (Cohen and Hoberman, 1983). According to Klein et al. (2004) people high in neuroticism will exhibit smaller networks. Additionally, in a social network jargon, extraverted and individualistic people have structure holes and network closure in their social network (Kalish & Robins, 2006). According to I. Lee, Kim & Kim (2005) mobile Internet use is clustered in a few key contexts, where contexts could possibly reflect on personality. To complete this, if we were able to access the type of webpages the user, that would allow us to recognise Extraversion, Openness to Experience and conscientiousness. More details can be found in the table below.

Behavior	Personality traits					Personality type	Source
	E	N	A	O	C		
High Internet social sites & female	very low	very high				woman with very low Extraversion and very high Neuroticism	(Amichai-Hamburger, 2005)

High SMS						young people	Bianchi & Phillips, 2001)
High Phone in general & other features						young people	Bianchi & Phillips, 2001)
Willing to reduce calls if prices go up	0.9	-0.7	0	0.7	0.1	Resillients	(Pöschl & Döring, 2007)
Less reluctant to fill information into registery than Resillients	-0.3	0.9	0.5	-1.1	-0.5	Overcontrollers	(Pöschl & Döring, 2007)
Switch off their phone for meetings more than Resillients	-0.3	0.9	0.5	-1.1	-0.5	Overcontrollers	(Pöschl & Döring, 2007)
Calling back as soon as possible after a missed call (50% more than average)	-0.3	0.9	0.5	-1.1	-0.5	Overcontrollers	(Pöschl & Döring, 2007)
Suppress caller identity rather more than Overcontrollers	0.9	-0.7	0	0.7	0.1	Resillients	(Pöschl & Döring, 2007)
Low call back as soon as possible after a missed call	0.9	-0.7	0	0.7	0.1	Resillients	(Pöschl & Döring, 2007)

Table 1. Qualitative correlation between mobile/web usage and personality types (combination of different personality traits or other demographics)

The personality trait level varies on a -1 to 1 scale or is divided into four different levels (very high, high, low, very low).

Behavior	Personality traits					Interpretation	Source
	E	N	A	O	C		
High Internet (leisure)	high				low		(Landers & Lounsbury, 2006)
High Internet (academic)					low		(Landers & Lounsbury, 2006)

High Phone in general	very high		low				(Butt & Phillips, 2008)
High calling	very high						(Butt & Phillips, 2008)
High changing wallpapers	very high		very low				(Butt & Phillips, 2008)
High changing ringing tones	very high		very low				(Butt & Phillips, 2008)
High SMS	low						(Butt & Phillips, 2008)
Highest SMS	high	very high	low		low		(Butt & Phillips, 2008)
Large social network & circles of friends	very high						(Amichai-Hamburger, 2005), Bianchi & Phillips, 2001)
Problem behavior (driving without handsfree)	very high					note: but also affected by young age and low self-esteem	Bianchi & Phillips, 2001)
Use mobiles for self-stimulatory purposes	high					High ratio of uncompleted activities vs completed activities	Bianchi & Phillips, 2001)
High gaming			low				(Phillips, Butt, & Blaszczynski, 2006)
Concerned with interpersonal relationships, that are based on the equal and honest exchange of information			very high			Equal amount of send & receive of MMS or SMS	Phillips et al., 2006
High Phone in general as "display"			very low			Using phone with people around	(Butt & Phillips, 2008)
Disvalue incoming calls	high		low			Received calls are shorter, High mute of incoming calls	(Butt & Phillips, 2008)

Less social anxious and lonely = prefers calls than SMS	very high					High outgoing calls & Low outgoing SMS	(Butt & Phillips, 2008)
Disagreeable people do not care what others think			very low			Take someone on hold for a long time	(Butt & Phillips, 2008)
High incoming calls			very low				(Butt & Phillips, 2008)
Search				high			(Butt & Phillips, 2008)
High length & depth of SMS indicate intimacy	high					High intimacy with many people might reflect extraversion	Soukup, 2000 from Password, 2006
Social network Bridges		very high				Individualist	(Kalish & Robins, 2005)
Strong network closure & "weak" structural holes. People who opt for network closure hold allocentric values, such as obedience, security and duty.	very high					less individualist	(Kalish & Robins, 2005), (Triandis, 1995)

Table 2. Qualitative correlation between mobile/web usage and the level personality traits.

The personality traits level is divided into four different levels (very high, high, low, very low). For example, the ***High phone in general*** *use case occurs for people with very high Extraversion values and for people with low Agreeableness, the rest of the personality traits are not correlated to the use case.*

3. Survey

In order to model of emotion from mobile user data, we should be able to explain more of emotions with mobile phone data. According to Eagle et. al.'s reality mining (2006, 2007, 2009a and 2009b) basic needs could be mapped from mobile user data, so let us try to find out whether the frequency of mobile phone events explains more of the emotional reactions (or vice versa), whether the respective selection threshold is high or low.

3.1. Methods

We designed a survey to collect the frequency of mobile phone events, related emotions and the participants' personality traits (see Figure 8). The survey was divided into 3 parts: a needs assessment questionnaire, a Big Five inventory and a short background questionnaire, which were glued as a form using Google docs and assigned a simple url using Blogger.

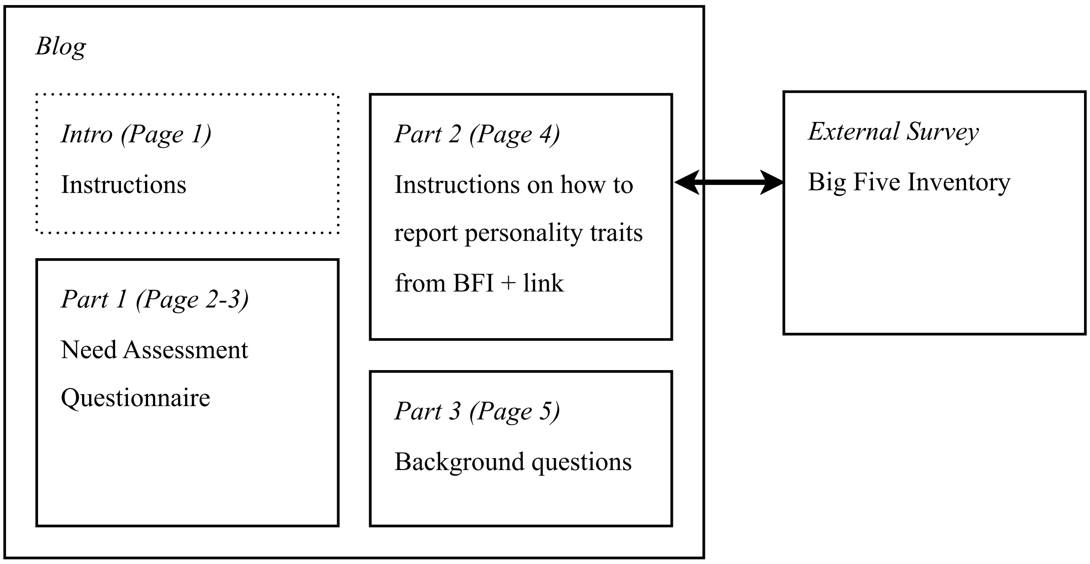

Figure 8. Survey structure

The needs assessment questionnaire was designed to the context of the mobile phone user, so that the potential needs are measured in the frequency of an event, and the subjective emotional effect when that event occurs. Collecting both sides would then allow us to verify this model in this context. The PSI model uses personality traits as thresholds for needs, giving a relativity when defining the emotional state. As the scope is recognising needs, the personality traits were found using a questionnaire rather than using data, which is never-the-less possible using other means (see chapter 2.3.2 for more details on how). Big Five inventories have been used for a long time in many different fields and many can be found on the Internet. Oliver D. John´s test of 45 items was used in this research.

3.2. Participants

In March 2010, 62 people participated of which 47 completed the survey properly (final N=47). The group had mostly grown up in western Europe (31 grown up in Finland, 6 in France, 2 in Sweden, 2 in UK, 1 in Greece, 1 in Germany, 1 in Switzerland and 1 in Australia) and was fluent in reading and writing English. Ages range from 22 to 64 years-old and genders are 23 females and 24 males. Since the participants were recruited using e-mail and Facebook, they are considered computer literate.

3.3. Procedure

The participants were contacted in five different ways: a) indirectly through the link of to the questionnaire was posted in my status 6 times over the period of 3 days (making about 200 impressions), b) directly through a Facebook message sent to three groups of 20 people, c) directly through an email sent to a group of people, d) asking friends to participate as I met them in real life or e) happen to chat with them on Facebook. Once the participant had accepted, s/he was directed to the blog address where the questionnaire was integrated. The questionnaire takes approximately 20 minutes. Written instructions were given just prior to the testing to complement the instructions printed above each questionnaire. If the participants' felt like it, they were able to enter their e-mail addresses in order to receive the abstract of the thesis, the emails were never-the-less separated instantly from the data to ensure that the data remains anonymous.

3.4. Measures

This research employed a Needs Assessment Questionnaire (NAQ), with which participants report the frequency of mobile phone events and the emotional reaction to that event, as seen in Figure 10. The Need Assessment Questionnaire is designed to collect the occurrence frequency of a given set of mobile phone events and the reported emotional reaction to those events (see Table 3).

High need for competence	(nCO 1) using at least 5 of the phone's features (nCO 2) using and following regularly the calendar (nCO 3) mobile phone crashes or does funny things (nCO 4) running out of battery in the middle of a phone call.
High need for certainty	(nCE 1) calls getting cut for some unknown reason (nCE 2) getting a call from an unknown or hidden number (nCE 3) having a prepaid subscription (nCE 4) operator has sometimes had to cut the line to get the bill paid.
High need for affiliation	(nA 1) sending group SMSs (nA 2) answering an SMS as soon as arrived, (nA 3) chatting through SMS (nA 4) using Facebook from phone (nA 5) own calls not getting answered (nA 6) calling close ones (nA 7) silencing phone when not wanting to be interrupted (nA 8) having many short calls with a set of people (nA 9) missing phone calls when the phone isn't silenced

Table 3. Needs reflected in mobile phone usage

Three dimensions structure the questions: need for affiliation (nA: four items), need for certainty (nCE: four items) and need for competence (nCO: nine items). Each question is scored on a scale from 1 to 5 (1: less than once a month or never, 2: once a month, 3: once a week, 4: 2-4 times a week, 5: every day or all the time) and rated on an emotional scale of 1 to 5 (1: I hate, 5: I love), with the exception of nCE3 which was a Yes/No question (Figure 9 illustrates a question in the survey).

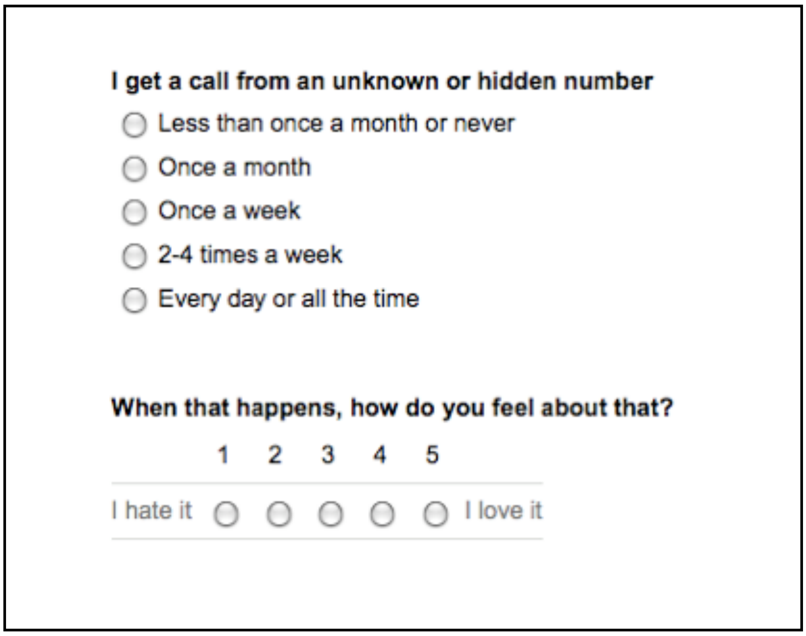

Figure 9. Example question from NAQ: nCE 2

In addition to the NAQ, the participants filled in a personality test called Big Five Inventory (BFI) (see Figure 10) and background questions. The BFI[9] is a 44-item questionnaire designed to measure the Big Five personality traits, which are Openness (O: ten items), Conscientiousness (C: nine items), Extraversion (E: eight items), Agreeableness (A: nine items), Neuroticism (N: eight items). Each question is on a scale from 1 to 5 (1: disagree strongly, 2: disagree a little, 3: neither agree nor disagree, 4: agree a little, 5: agree strongly).

[9] UC Berkely psychologist Oliver D. John's online BFI, found at http://www.outofservice.com/bigfive/

I see myself as someone who...

1. ...Is talkative
Strongly Disagree 1 2 3 4 5 Strongly Agree

2. ...Tends to find fault with others
Strongly Disagree 1 2 3 4 5 Strongly Agree

3. ...Does a thorough job
Strongly Disagree 1 2 3 4 5 Strongly Agree

4. ...Is depressed, blue
Strongly Disagree 1 2 3 4 5 Strongly Agree

5. ...Is original, comes up with new ideas
Strongly Disagree 1 2 3 4 5 Strongly Agree

Figure 10. Example question from BFI (from John, 2009)

The personality traits values are mapped to the Selection Threshold of the the respective need using the same weight and logic described in Table 4 for each personality trait depending on how important it is to the need, based on psychological definitions (more details are explained in section 2.3 on these definitions).

Need for affiliation	**(0.75) Extraversion** **(0.25) Agreeableness (Reversed)**
Need for competence	**(0.25) Extraversion** **(0.25) Agreeableness (Reversed)** **(0.25) Conscientiousness** **(0.25) Openness to experience**
Need for certainty	**(1/3) Agreeableness (Reversed)** **(1/3) Conscientiousness** **(1/3) Openness to experience (Reversed)**

Table 4. Mapping of personality values (Nazir et. al., 2009)

By simply weighting and summing up the personality factors, we are able to define the selection thresholds of each respective need, which is where the user starts to experience a drive from that given need. For example, Selection Threshold of Need for Affiliation = (0.75) Extraversion + (0.25) Reversed Agreeableness.

3.5. Results and Analysis

3.5.1. Summary of the data

From the personality traits collected in the survey (see Appendix B for more details on the data), four of the five personality traits had means around the average score whereas the fifth, Conscientiousness, had a mean slightly below average. The selection threshold values for the needs were then derived. Figure 11 shows us a clear distinction between the levels of low and high thresholds.

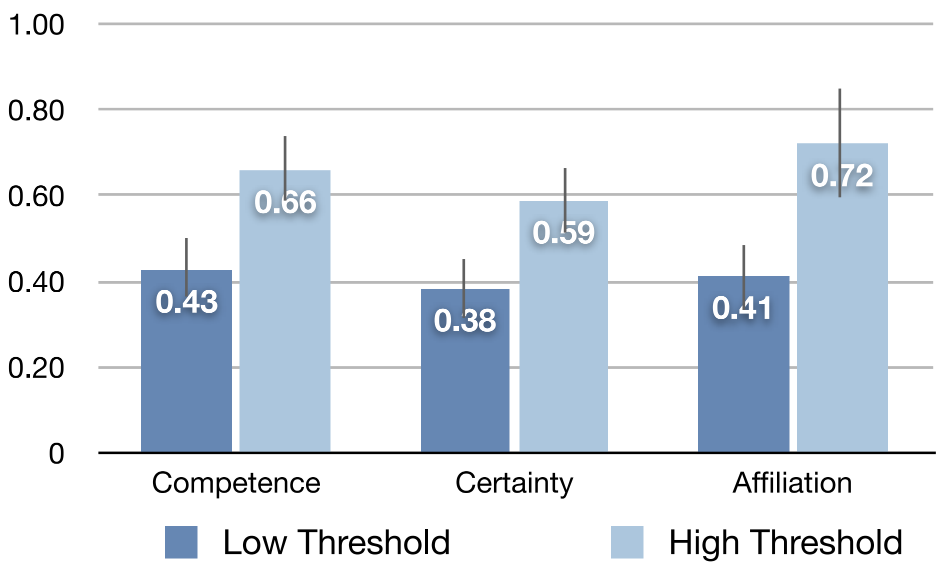

Figure 11. Mean threshold of specific needs *and Standard deviation.*

From the data from the Need Assessment Questionnaire represented in Figures 12a, 12b, 13a and 13b, it is apparent that the frequency of mobile phone events hardly vary between the high and low respective selection thresholds. There is never-the-less clear differences in emotional reactions between questions.

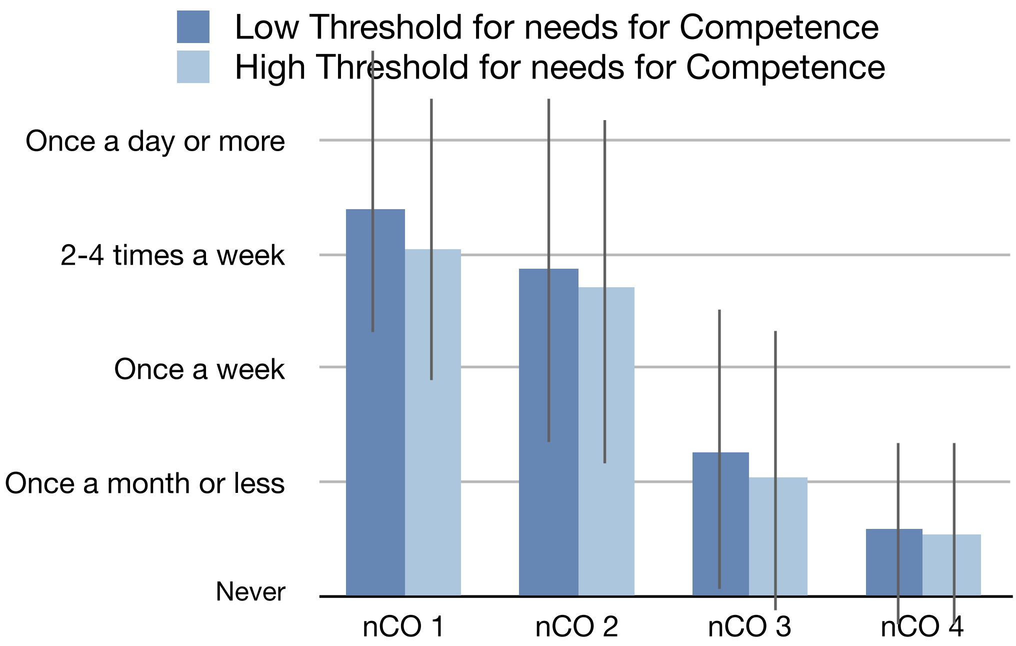

Figure 12a. Frequency of mobile phone event for the people with high and low threshold of need for Competence *and Standard deviation.*

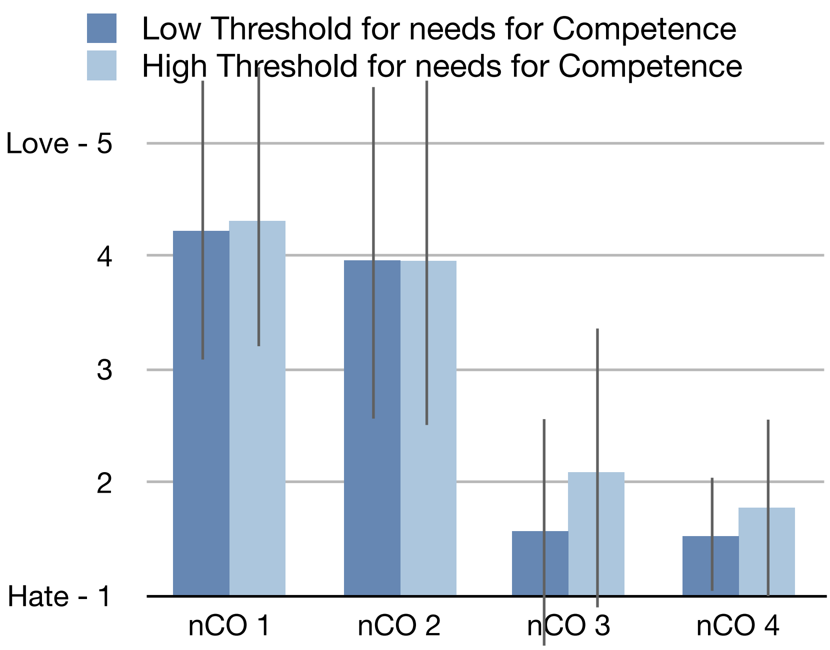

Figure 12b. Emotional reactions to mobile phone events for the people with high and low threshold of need for Competence *and Standard deviation.*

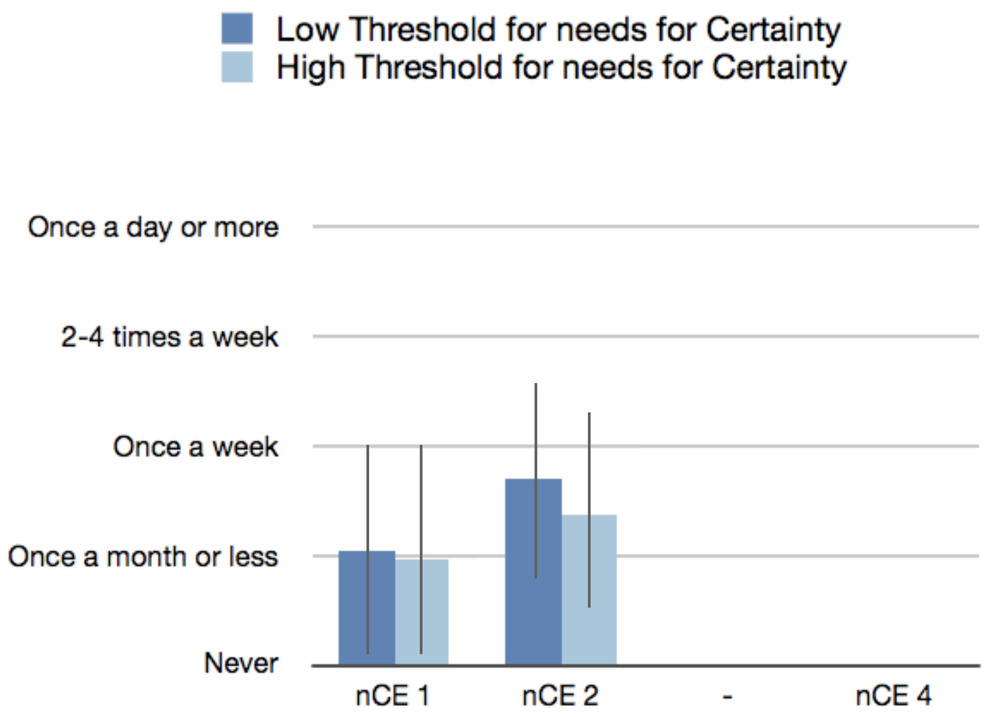

Figure 13a. Frequency of mobile phone event for the people with high and low threshold of need for Certainty *and Standard deviation.*

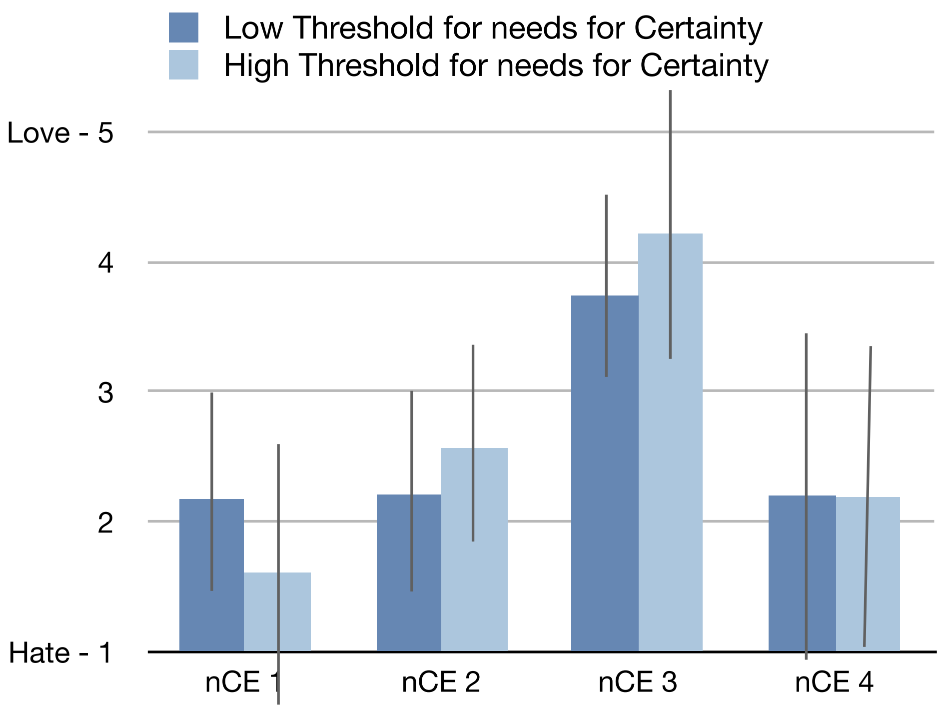

Figure 13b. Emotional reactions to mobile phone events for the people with high and low threshold of need for Certainty *and Standard deviation.*

Considering the questions in the Need Assessment Questionnaire (see Table 4) were hand picked, it is worth evaluating how sensible the data is. First, the four questions supposed to reflect competence (nCO 1, nCO 2, nCO 3 and nCO 4) are according to Table 5 and 6, distinctively forming two groups: nCO 1 and nCO 2, which are by nature closely related and are about the user's habits, these are clearly related to the user's technological competence; and nCO 3 and nCO 4, which are, on the other hand, events that are dependent on the stability and usability of the handset, which influences the felt need for competence. Table 5 indicates that these last two questions are, as anticipated, low. This is a general emotional reaction to bad stability and usability, but one could expect less negative emotional reaction coming from the users with technological competence and maturity as they are aware of the cause of the negative event. This would expectedly slow down the decay of needs for (technological) competence.

Secondly, the two first questions about the need for Certainty (nCE 1 and nCE 2) are related to to the presence of unknown variables (calls cutting for unknown reasons and incoming calls from unknown or hidden numbers) and according to Figure 13b the reported emotion reaction seems to vary among the population, even the events occurrence vary in the opposite direction than the change of emotional reaction. According to the third questions nCE 3, only 4 out of the 47 participants have a prepaid subscription, which is aligned with Finland having 9% of mobile users as prepaid in 2007 (Mervi, 2007), but according to Figure 14b the emotional state attached to that seems more positive than negative, which would slow down the decay of need for certainty as this could be interpreted as a consequence of the strengthening the sense of security.

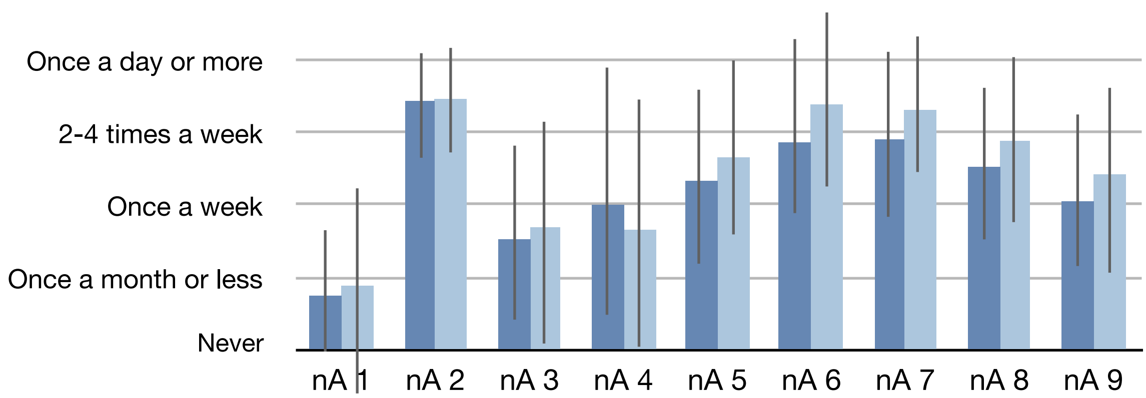

Figure 14a. Frequency of mobile phone events for the people with high and low threshold of need for Affiliation *and Standard deviation.*

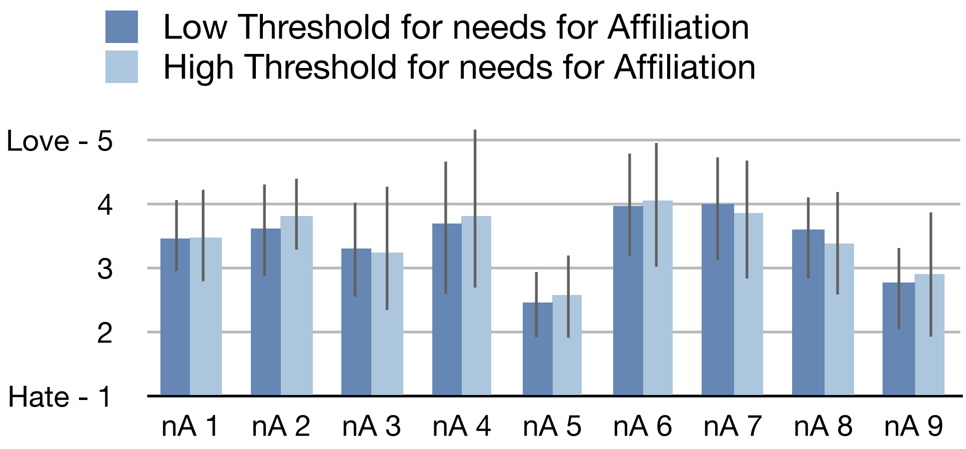

Figure 14b. Emotional reactions to mobile phone events for the people with high and low threshold of need for Affiliation *and Standard deviation.*

If we look at each event separately, we can notice that *group SMS* (nA 1) seems like a generally rare activity and doesn't really reflect any strong emotion as it occurs. The average frequency of *answering soon as one get a message* (nA 2) is between every time to 2-4 times a week, but even though the emotional reaction is a bit over average, the people with higher threshold of need for Affiliation seem to react more positively about it, which makes sense as people with a strong need for Affiliation attach importance to personal interaction. *Chatting through SMS* (nA 3) occurs a bit less than once a week, but is slightly more frequent for people with higher threshold, but it varies so much that it isn't considerable. The variance of the usage of facebook on the phone (nA 4) is so large and the size of the group so small that not much else can be said other than usage varies a lot. Not having one's calls answered (nA 5) is the event which has the lowest emotional reaction in this category of need. Calling close ones (nA 6) is the event which has the largest apparent difference between people with high and low threshold of need for Affiliation, but then again the emotional reaction doesn't different between the two types. Silencing the phone when not wanting to be interrupted (nA 7) is a sign of respect for people around you, so it makes sense that people with high Affiliation threshold do that more often than those with lower. Many short calls with a set of people (nA 8) has also a more common habit of users with higher threshold, but not much more. Finally, users with the high threshold miss a bit more often calls than the ones with lower threshold (nA 9). Overall, the data has a relatively large variance (from $\sigma = 0.53$ for nA 3 to $\sigma = 2.96$ for nA 4) and from small group of N=21 to N=27.

3.5.2. Comparisons

The *null hypothesis* implies that there isn't any correlation between mobile phone data and the emotional reactions whether people have high or low threshold of needs, technically that there is no significant difference between the correlation coefficient and the Spearman rho = 0.

Ho: r = rho = 0

Ha: r ≠ rho = 0

We therefore looked for a statistical correlation between the mobile phone event and the emotional reaction and tested whether there was a significant difference between the correlation and rho = 0.

As Table 5 shows, there is almost a significant between the frequencies and emotional reactions throughout the group in the use of at least 5 mobile phone features nCO 1 ($p = 0.0013$), the regular usage of calendar on the phone nCO 2 ($p = 2.70E-5$), sending group SMSs nA 1 ($p = 0.0025$), nA 2 ($p=0.046$), chatting through SMS nA 3 ($p=0.014$), the use of Facebook on the mobile nA 4 ($p = 8.00E-06$) and calling close ones nA 6 ($p = 0.0023$) throughout the group, silencing one's phone when not wanting to be interrupted nA 7 ($p = 0.017$) and having many short calls with a set of people nA 8 ($p=0.015$). In Table 6, there was almost a significant difference between the correlations for people with high and low threshold in nCO 1 ($p = 0.08$) is the event with correlations between users with high and low threshold of the respective need, in this case the need for Competence.

	r	r^2	n	*z*	p (2-tailed)	Difference (p < 0.10/17 = 0.006)
nCO 1	0.45	0.20	47	3.22	0.0013	Yes
nCO 2	0.56	0.31		4.20	2.70E-05	Yes
nCO 3	-0.2	0.04		-1.34	0.18	No
nCO 4	-0.11	0.01		-0.73	0.47	No
nCE 1	-0.32	0.10		-2.21	0.027	No
nCE 2	-0.20	0.04		-1.31	0.19	No
nCE 3	0.00	0.00		-		No
nCE 4	0.00	0.00		-		No
nA 1	0.43	0.18		3.02	0.0025	Yes
nA 2	0.29	0.09		2.00	0.046	No
nA 3	0.35	0.13		2.45	0.014	No
nA 4	0.59	0.34		4.46	8.00E-06	Yes
nA 5	-0.09	0.01		-0.60	0.55	No
nA 6	0.43	0.19		3.05	0.0023	Yes
nA 7	0.35	0.12		2.39	0.017	No
nA 8	0.35	0.12		2.44	0.015	No
nA 9	-0.21	0.05		-1.44	0.15	No

Table 5. Significant difference of the correlations between frequency and emotional reactions to mobile phone events for all participants

Since the two-tailed test is with 10% significance interval and the two groups of high and low threshold of need for Competence (N1=23 and N2=24) are relatively small, a more rigourous test should be conducted. One way to make multiple testing more rigourous is to set a Bonferroni corrected p-value (here $p<0.1/17=0.006$). In Table 5, there are correlations that met this level: the ones between the frequencies and emotional reactions throughout the group in the use of at least 5 mobile phone features nCO 1 ($r = 0.45$), the regular usage of calendar on the phone nCO 2 ($r = 0.56$), sending group SMSs nA 1 ($r = 0.43$), the use of Facebook on the mobile nA 4 ($r = 0.59$) and calling close ones nA 6 ($r = 0.43$) throughout the group. In Table 6 no correlation met this level of correlation.

	r_{low}	n_{low}	r_{high}	n_{high}	z	p (2-tailed)	Difference (p < 0.10/17 = 0.006)
nCO 1	0.66	23	0.24	24	-1.75	0.080	No
nCO 2	0.50		0.63		0.63	0.53	No
nCO 3	-0.36		-0.11		0.85	0.40	No
nCO 4	-0.16		-0.11		0.16	0.87	No
nCE 1	-0.16	23	-0.53	24	-1.37	0.17	No
nCE 2	-0.14		-0.37		-0.79	0.43	No
nCE 3	0.00		0.00		-		No
nCE 4	0.00		0.00		-		No
nA 1	0.39	21	0.43	26	0.15	0.88	No
nA 2	0.27		0.32		0.17	0.87	No
nA 3	0.14		0.45		1.09	0.28	No
nA 4	0.67		0.51		-0.79	0.43	No
nA 5	0.23		-0.21		-1.42	0.16	No
nA 6	0.30		0.56		1.03	0.30	No
nA 7	0.45		0.25		-0.73	0.47	No
nA 8	0.44		0.25		-0.69	0.49	No
nA 9	-0.31		-0.17		0.47	0.64	No

Table 6. Significant differences of the correlations between frequency and emotional reactions to mobile phone events for people with high and low level thresholds

3.5.3. Reliability

The validity of the questionnaires is something that seems to be at stake. The BFI and the background questionnaires were relatively straight forward and can be considered as valid. But looking at correlation between the NAQ items that were supposed to support the same need, the items did not successfully measure the needs there were assigned to. The NAQ was derived from a NAQ which had a different scale and different logic in the items, so it seems that the content isn't quite represented in the type of behaviour that was chosen. Items nCE 3 and nCE 4 didn't vary at all among the participants, which makes them poor at reflecting the respective need for certainty and additionally leaves only two items to reflect that need.

The participants was a relatively good sample considering, the cultural factor was meant to remain relatively stable. 32 of the 47 participants had grown up in Finland, 6 in France and 2 in UK, 2 in Sweden, 1 in Switzerland, 1 in Greece , 1 in Germany and 1 in Australia. We could use the Finland's Geert Hofstede cultural dimension score for the population from Finland, but considering the rest of the participants are from around western Europe and 1 from Australia, we couldn't use the country level scores for such small groups, as the country's culture isn't representative of the individuals' culture from that country.

The flow of the survey wasn't very smooth as the participant was expected to jump from one questionnaire to the following by copy pasting the address or following a link which was placed in a nontrivial location. Additionally, they were asked redundantly certain demographic details in both questionnaires, due to their being independent. Finally, the user was supposed to copy the result of the personality test and paste it into the original questionnaire. This consequently followed in participants either not completing the BFI questionnaire, or not coming back to the original questionnaire and therefore not submitting any data at all.

The NAQ has a Gunning Fog Index of 5.55 making it readable by people with a very basic English. Considering people who participated in the test all had higher education and spoke fluently English, I don't see the language being a contributing in affecting the validity of the test.

A pilot test was conducted, but only with 3 people. Overall, there seem to be enough variation and all the users did complete the entire survey without any reported troubles other than small typos.

3.5.4. Shaping Hypothesis

At the outset of the survey the null hypothesis was that there isn't any correlation between the frequency and the emotional reactions to certain mobile phone events. We looked at people with high or low threshold of the respective needs or in general.

Independently of the level of need Threshold, *using at least 5 mobile phone features* (r = 0.45), *using regularly the calendar on the phone* (r = 0.56), *sending group SMSs* (r = 0.43), *using Facebook on the mobile phone* (r = 0.59) and *calling close ones* (r = 0.43) all had a significant correlation with the respective emotional reaction the users had. But no event had a significant emotion-frequency correlation that also had a significant difference between people with high or low level in the respective threshold of need, which indicates either that no events selected did not have anything to do with those needs or that the Nazir's mapping was not appropriate to mobile phone context. More study is needed especially on what events could possibly be best linked to the needs of Competence, Certainty and Affiliation.

A hypothesis made on the basis of this survey is presented below:

Certain mobile phone events affect the user's emotional state.

The evidence, which supports the construct, is listed below:

- 5 of the 17 mobile phone events researched in this survey had a frequency which was significantly correlated to the emotional reaction the users' had to those events.
- 1 of the 17 mobile phone events researched (using at least 5 mobile phone features) in this survey had a frequency which was almost significantly correlated to the emotional reaction of people with high threshold of the need for Competence, but also had a almost significant difference from people with low threshold of the need for Competence (however with a single test p-value).

4. Discussion

As we saw in the Background section, there is a variety of models of emotions and recognition methods exist, but few have been used mobile phone context. The type of data available is clearly the main constraint to the recognition of emotions on mobile phones.

4.1. Mobile data

4.1.1. Taxonomy

Using the channels of emotion expression collected in the literature study and Verkasalo's (2007) list of usage activities, data available from mobile phones was put in a hierarchical classification in Table 7 to clarify what data could be used with what model type. Channels did overlap, which makes it difficult to make a sound taxonomy. Considering the model types available to date, only personality can be recognised from product usage, which would make emotion recognition more complex. Based on the literature research the recognition of needs at such a level doesn't seem to have been done and considering the absence of correlation in the research we conducted would require deeper psychological analysis to map data to needs.

channel	source	type	recognised	data
acoustic	mobile	communication	emotions	voice
body language	mobile	context	emotions	BT neighborhood
product usage	mobile	communication	personality	voice to all communicatior
				SMS to all communication
				Calls per weeks
				outbound voice call durati
				SMS replied
				Outbound SMS lengths
				Outbound voice contact er
				outbound SMS entropy
				Outbound MMS entropy
				mute & send immediate re
				Incoming calls
				Call duration
				time until call returned
				messaging
				messenger
		leisure	personality	themes
				gaming
				URL
		content	personality	Number of contact in phor
				length of contact details
		general	personality	time since last use
		consumption	mood	purchases
	operator	communication	personality	voice to all communicatior
				SMS to all communication
				Calls per weeks
				outbound voice call durati
				SMS replied
				Outbound voice contact er
				outbound SMS entropy
				time until call returned
				Incoming calls
				Call duration
mental	mobile	content	personality	SMS content
			mood	SMS content

Table 7. Data Taxonomy

4.1.2. Usable mobile user data

In order to leave options to use as wide a variety of the data available from the mobile phone as possible, we collected all the feasible methods that could be used to model or recognise some of the elements that would help in recognising or modelling emotional states. As denoted by red lines in the Figure 15 only a few models allow us to extract valuable information from these types of data.

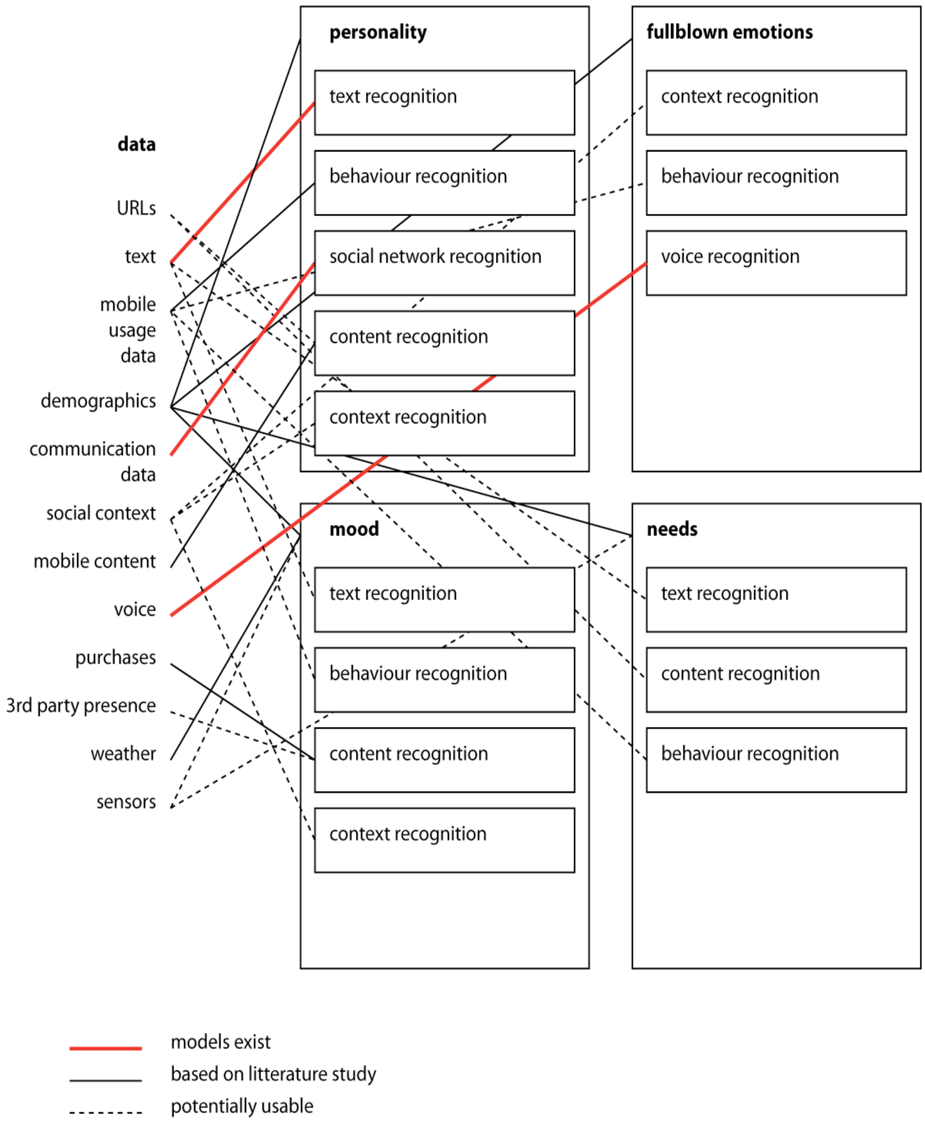

Figure 15. Usage of the mobile phone data in the recognition process

4.2. Conceptual model of emotions recognition

The model that is proposed in Figure 16 takes into account two main elements: the source of emotional change and modulators. These sources of emotional change are events or patterns of events which trigger emotional responses. These responses affect the emotional state of the user. Going into modelling how it does would require us taking into account the theory of mind (recursive beliefs about self and others), culture and long-term memory and knowledge, which we don't. According to the our survey, there definitely is emotional reactions to mobile phone events. Subjective well-being was measured and linked to distinctive activities by Kahneman and Krueger (2006), which by definition clearly is a source of positive affective phenomena. The concept of modulators is based Dörner's model which uses Big Five personality traits and basic needs to amplify, suppress and even define the emotional state, though without taking into account any theory of mind (Bach, 2009). Never-the-less when needs are unmet, a homeostatic phenomena provokes a behavioural reaction to fulfil these needs, which is usually accompanied with stress, and therefore an amplification or suppression of affective states. A similar threshold for needs as Dörner derives from personality traits in his PSI model would allow the calculation of that limit which defines when exactly the needs are unmet. As seen in the survey, there seems to be a correlation between the usage frequency and emotional reaction to the respective mobile phone event, which would allow the modelling of emotional changes. Additionally, if we keep in mind that the user has a theory of mind (recursive beliefs about self and others), modelling emotions as such feels suddenly naive, especially when social emotions are strongly dependent on such beliefs. Even though mobile phones have taken a much more general role in our lives, its main purpose still remains communication.

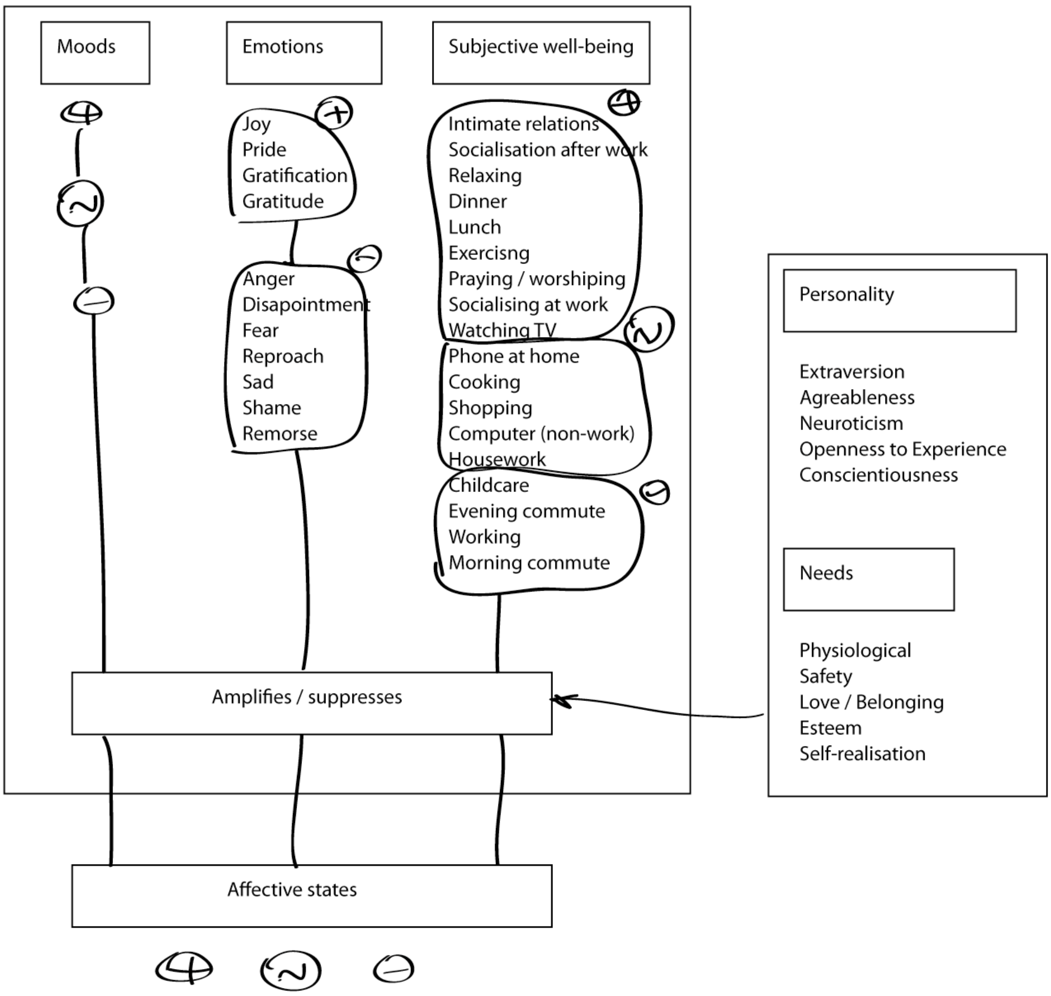

Figure 16. Proposed model of emotions

4.2.1.Multimodalities

People use by nature several sources to assess a person's emotions, including causal information on both the context and the person's relevant personality traits, as well as the already mentioned symptomatic information on the person's bodily reactions, it wouldn't make sense modelling human emotions with only one channel. But it is common that this information is incomplete or even contradictory, making emotion assessment a task with riddled uncertainties for humans and computers. For that reason, using a high variety of sources of information would help in getting a overall view of the context and person, and therefore avoiding situations where uncertainties would make the recognition biased. Already in 1992, we knew how important of the use of multi-modalities (or features) are when trying to have accurate recognition of emotions, as Ambady and Rosenthal (1992) observed that both facial expression and body gestures were important for humans to judge behaviour cues. The use of these two modalities increased accuracy by 35% compared to the face alone, whereas the use of only facial expression was 30% more accurate than the body alone and 35% than the voice alone.

Cowie & Schroeder (2005, p.311) describe emotions as being "intrinsically multifaceted" and continues with "To attribute an emotional state is to summarise a range of objective variables. Hence, no one modality is indispensable. Equally important, there is no measure that defines unequivocally what a person's true emotional state is", which condemns the use of single modality and emphasises the importance of the fusion of modalities to perform successful and accurate emotion recognition. Accuracy seems to be obtained indeed by these means, not only for emotional recognition but also of the wider spectrum of affective phenomena (Borkenau, Mauer and Rieman , 2004).

The recognition of affective phenomena based on mobile user data is such a novel field that this is more prone to error, making the need of such triangulation even higher. Finally, the analysis of multiple will require sound models for the fusion of these.

It is common practice, according to Pantic and Rothkrantz (2003), to process data separately and only combine them at the end. Pantic and her colleagues acknowledge the fact that experimental studies have shown that late integration (decision-level data fusion) provides higher recognition scores than an early integration approach, but never-the-less proposes to have the input data processed in a joint feature space and to a context-dependent model, in the same manner than human perception. So once different recognition methods are clear, they should only then be combined in a multimodal model.

4.3. Ethics

Actually, it is important to distinguish between expressed emotions and aroused emotions. (Mera & Ichimura, 2006) calculated these expressed emotions according to the user's personality, which brought to my mind that the general mood is something that the user is not always interested to share. It becomes therefore an important ethical issue, that if moods are recognised, that it is only for a personal use, and would stay within the phone! Different uses were earlier described as mobile marketing filtering or mood tracking. A solution to satisfy the need to express the user's expressed emotion proactively is follow the model (Mera & Ichimura, 2006) designed based on the user's personality in parallel to the mood.

5. Conclusion

5.1. Reliability

The thesis stretch over 3 years, during which a lot happened in such booming fields that are emotion recognition and mobile phones, which caused some slight inconsistency in the research contexts referred to. This novel and experimental field did consequently have information on the subject scattered among different fields, which made the material vary in terms of goals, methodologies and even terminology.

The reliability of the NAQ is questionable, considering the poor results. Thus the use of the Bonferroni correction, that it is known to be too conservative for variables that are mutually correlated, combined with a smaller size sample that was used and keeping in mind the experimental stage of the PSI model, it not that big of a surprise that it wasn't a total success.

5.2. Answers to Research Question

The answer to the relevant research questions are presented below:

- What mobile phone data would best suit the modelling of emotional states?
  - The taxonomy of mobile data created in Section 4.1.1 shows the different types of data that could suit in the modelling or recognition of emotional states. There is never-the-less a clear distinction between modelling and recognising, each would require different approaches to extract emotions.
- How well could the most appropriate model of emotion perform with mobile phone data?
  - The frequency of mobile phone events were researched in the Section 3 and one event out of 17 events was found to support the essential part of Dörner's PSI model. So it seems the Dörner model couldn't perform well. Though the high number of variables that need to be defined to calculate emotions in Dörner's model, and the size of the population sample used in the survey, it is most likely that more research would be needed to have a higher certainty on this conclusion.

- Would a computational model of emotions be feasible in the context of mobile phone?
  - Mobile phones have over the last 4 years been equipped with high processor power. Using a computational model is feasible to compute the change in emotions rather than the state itself, as there isn’t yet any model of emotions that could be used to model real user’s emotional states from user behaviour, but only those of Virtual agents. A conceptual model was proposed in Section 4.2 and could be the base of that computational model.

Finally, the answer to the main research is presented below:

What mobile phone user behaviour could be used to model emotional states?

Mobile phone users seem to be reacting emotionally to a considerable amount of different mobile phone events. But without having access to the user’s past experience and other tacit knowledge, emotional states won’t be able to be modeled as such. Never- the-less behaviors that could possibly be used in the modeling the change in emotions are the ones related to technological competence and the need for affiliation.

5.3. Suggestions

This study targeted the modelling and recognition of emotions on a high level in order to understand how humans and machine do that today. Theories and computational models are still far apart from each other, since theories are so complex. The study is a window into the world of emotion models and the presence of the mind is the reason why it is so complex. The survey clearly demonstrated that data mining has its place in the modelling of emotions in the context of mobile phone.

The hypothesis in Section 3.5.3 is offered as a course of action for dwelling in mobile phone data mining.

5.4. Recommendations for Further Study

The result of the survey confirmed the need for a larger scale collection of data from the handset themselves, but would additionally require to randomly collect emotional responses straight from the handset, which would allow a lot reliable results. It is also recommended to conduct the future research on a sample with to a narrow Geert Hofstede cultural dimension, since culture is clearly a modulating factor. An example is how a user from a collectivist culture would have a strong need to answer or return phone calls, even though the context isn't appropriate. But the such behaviour would define a level of disrespect. Considerably more work will need to be done to determine if the PSI model is adequate for modeling in mobile phone context. Beyond the initial look at emotions in the mobile phone context there are many steps, which can provide further information. As some needs have been identified in the survey, applied research on customer insight data mining surely benefits looking into recognising basic needs, the first step being to research what the different levels of needs resolution would be. Defining the needs in terms of usage patterns should be the focus of further study.

From a privacy and ethics point of view, discussions need to be held on what data would be considered as acceptable to use even when anonymised.

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Appendix

Appendix A – Description of application areas

Here's a list of areas which could benefit of the recognition of emotional states from mobile phones:

Development of new mobile phones: Every user has different levels of needs. Being able to understand what is associated to a boost or a decrease in mood could help in the decision of what features should be part of a phone for a specific user type.

Self-regulation: Being able to regulate one's emotions is something people thrive toward. By identifying the turning point of a full-blown emotion could allow people to learn how to regulate their emotions before negative emotions outburst.

Personalisation: People have tendencies to personalise their phone, ranging from the colour of the phone to the ringing tone, via backgrounds, profiles or skins for applications like the web browser Opera mini 2.0. Different personalisation features or options could be proposed by the mobile phone to its owner, when s/he would like to change something. Both mood and personality could bring personalisation and/or emotional colouring of system messages or interaction, once approved by the user.

Hyper targeting: Marketing and advertising are areas, which would benefit enormously of affects and personality recognition. According to (Gardner, 1985), mood states have a direct and indirect effect on behaviour, evaluation and recall (see Figure A1), which would allow marketers to choose the optimal emotional state when the end-user should receive an advert. Such insight in one's customer base would also allow a company to produce the right marketing content and products with an appropriate emotional colouring for their customers, and advertise the right product to the right people.

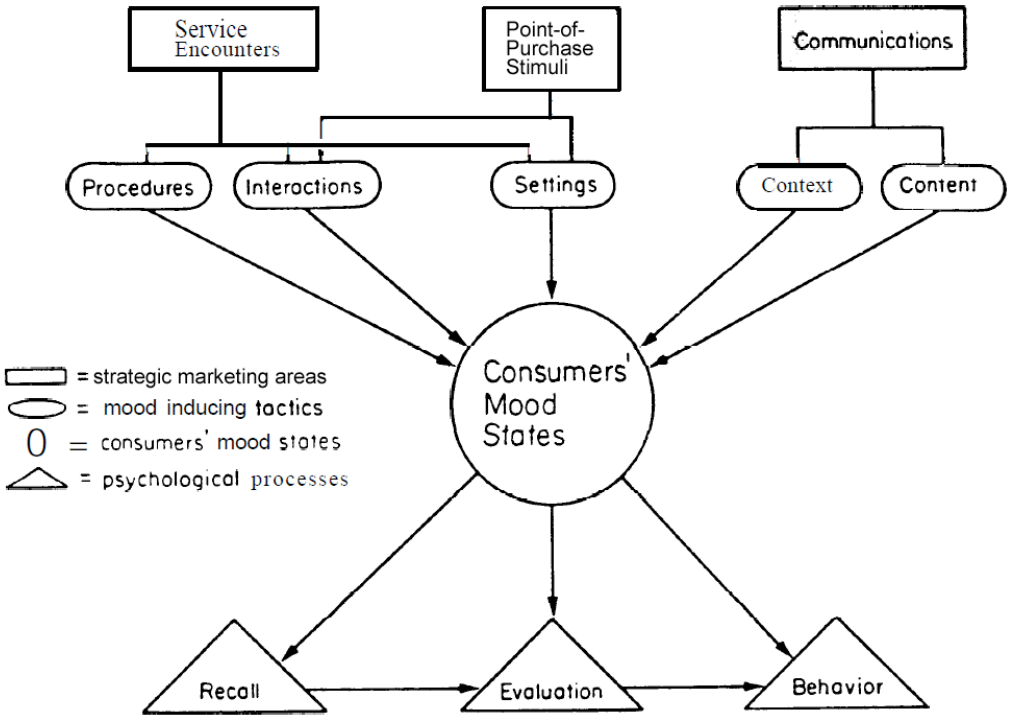


Figure A1. Conceptual model of the role of mood states in consumer behavior (from Gardner, 1985)

Alerting: As we just shortly discussed, emotions and cognition are strongly linked. Consequently, any task requiring high cognitive resources will benefit from affective intelligence. Pilots, drivers or surgeons could themselves or their supervisor be alerted of affects interfering with their performing. Another application could be within communities or families. If a member of the staff or family would have been in a bad mood for too long, other members or the person him/herself could get a message alerting for avoiding side effects.

Interruption: Interruption rates during a normal working day are recently reaching amazing records[10], making everybody's life very inefficient and stressful. Additionally, people communicate through many channels through their mobile phone (voice, video, SMS, MMS, e-mail, IM, PTT), which increases the probability of interruption, making life extremely hectic. SPAM have made people really sensitive to interruption, as it has been flooding almost every Inbox on the Internet with unwanted adverts. Consequently, mobile marketing has the challenging task not to become mobile SPAM.

10 Creating Passionate Users blog-entry on how impossible interruption rate can become:
http://headrush.typepad.com/creating_passionate_users/2006/12/httpwww37signal.html

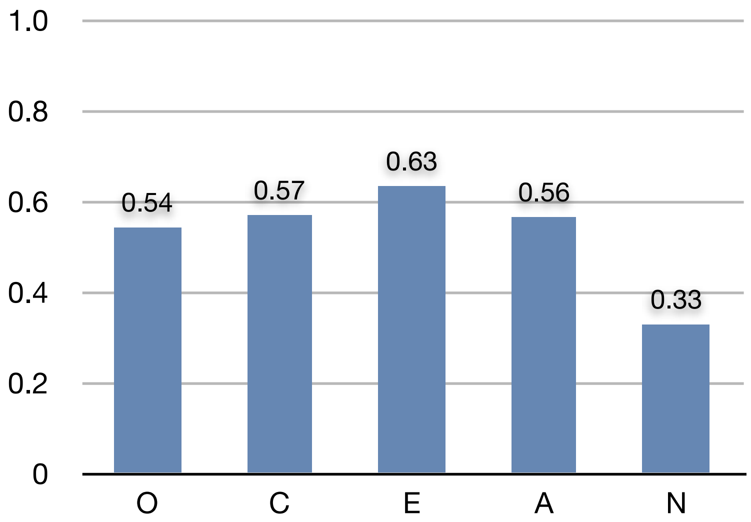
It is known that when someone feels blue, s/he might want to spend some time alone, or when a user is in a specific mood the mobile phone would act as a filter for ads, calls, interruptions, or certain types of messages. Knowing the user's context, mood and personalising her/his content are key features in allowing him to live an efficient life with an optimal stress level.

Augmented human judgement: Human perception is by definition subjective, as cognition is affected by intelligence, memory, personal context and emotional response (Bower, 1981; Ekman & Friesen, 1975; Ekman, 2005; Forgas, 1995; Izard, 1977). Such perception is not optimal, when the recognition of affect influences the hospitalisation or medication prescription of people. It should therefore be objective and accurate. Having the possibility to have an agent collect data about signs of affects under a longer period of time, could allow the doctor a more accurate detection and understanding of the patient's potential emotional disorder, such as schizophrenia or depression. Such an agent could be running unobtrusively in the background in the mobile phone, and even complemented with a diary allowing the patient either to record sound clips or write entries.

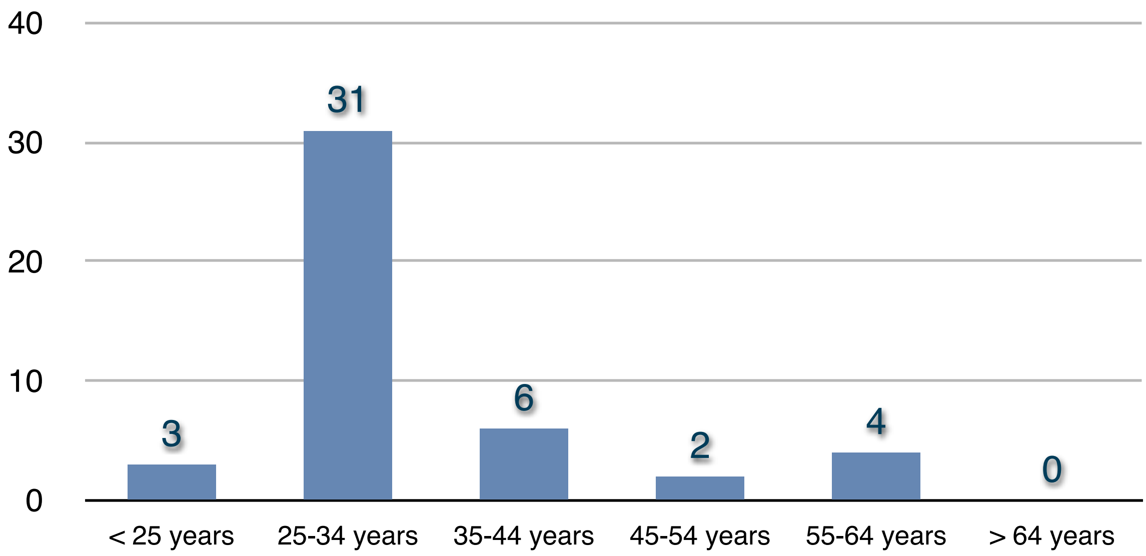
Appendix B – Details of the Data Sample

	Total
Participants	47
n/a	0
Female	23
Male	24
n/a	
< 25 years	3
25-34 years	31
35-44 years	6
45-54 years	2
55-64 years	4
> 64 years	0
Grown up in...	
Finland	31
France	6
Sweden	2
UK	2
Greece	1
Switzerland	1
Australia	1

Mean personality traits



Age distribution



Appendix C – Mobile applications used to collect data

Application	**Data type**	**Data points**
Nokia 360	Any mobile usage data	
ContextPhone (Raento et al., 2005)	Location	GSM or GPS
	User interaction	active applications, idle/active status, phone alarm profile, charger status, and media capture
	Communication behaviour	call and call attempts, call recording, sent and received SMS, and SMS content
	Physical environment	surrounding Bluetooth devices, Bluetooth networking availability, and optical marker recognition (using the built-in camera
SocioXensor (Mulder et al., 2005)	User experience data	subjective information such as opinions and feelings
	Human behaviour and context data	raw, objective data about user behaviour and context (e.g. location, proximity, activity and communication) that is captured unobtrusively through technologies on contemporary mobile devices such as PDAs and smartphones (e.g., GSM Cell-IDs, GPS location data, Bluetooth device detection, audio microphone, call logs, contact data, and calendar data).
	Application usage data	raw, objective data about the usage of the application that is being studied. The raw data may range from low-level keystrokes and screens to high-level application events

Application	Data type	Data points
Feel*Talk (2006) by Panasonic & NTT DoCoMo	voice	tone and pattern
ContextWatcher (http://contextwatcher.web-log.nl/)	bluetooth	Bluetooth ids are manually associated to values such as activity, mood or transport.

Appendix D – Collectible relevant mobile phone data

This is a list of existing applications that collect behavioural, social, usage or raw data from mobile phones.

data type	Name	description of usage	Electronic Contact
Bluetooth neighbourhood	Botsbot	The application keeps track of the other Bluetooth devices the user meets during the day.	www.botsbot.com
Bluetooth neighbourhood	contextwatcher	The user can associate her/his experiences with Bluetooth devices.	http://contextwatcher.web-log.nl/
Emoticons in messages	Panasonic VS3	When receiving usual text smileys, the user has an external LED blinking on the phone with various colours.	http://www.mobile-review.com/review/panasonic-vs3-1-en.shtml
Bluetooth neighbourhood	Jaiku	Shows to the contacts the number of friends and other Bluetooth devices around the user.	www.jaiku.com
Calendar entry	Jaiku	Displays if the user is busy, by showing the last and next calendar entry for her/his contacts to see, or only a busy status.	www.jaiku.com
Phone usage	Jaiku	Shows if the user uses her/his phone at the moment or how many minutes since s/hedid.	www.jaiku.com
Location (manual/cell ID)	Jaiku	Displays the current location of the users to her/his contacts.	www.jaiku.com
Ringing profile	Jaiku	Displays the name of the ringing status and a colour code (red-orange-green) of the users to her/his contacts.	www.jaiku.com
Black list, contacts, Bluetooth neighbourhood	Ringing profile	Fits your phone ringing tones according to your context or contact.	
Voice tones & patterns	Feeltalk	Panasonic and NTT DoCoMo have developed a phone which indicates your mood based on the voice analysis (tones & patterns) and indicate it by a colour on the phone. This handset can express the mood (happy, stressed or angry) of a conversation in 45 different types of animation and illumination after the call. Panasonic claim this is useful to decipher your mood during conversations. Even though the LED is oriented towards the outside world, indicating the mood of the user.	http://crave.cnet.com/8301-1_105-9663597-1.htmlhttp://crave.cnet.com/8301-1_105-9663597-1.html http://panasonic.jp/mobile/p702id/feel_talk/index.html

data type	Name	description of usage	Electronic Contact
Tags	Feeltalk	These can also be retained as icons on your Call History and Call Memory.	http://crave.cnet.com/8301-1_105-9663597-1.htmlhttp://crave.cnet.com/8301-1_105-9663597-1.html http://panasonic.jp/mobile/p702id/feel_talk/index.html
Tags	Pictures, contacts	Tags can give valuable description/classification. E.g. who the contact is.	
Background images, colour, animation, animated text or music	Deco-mail NTT	communicate a mood	http://www.nttdocomo.co.jp/english/service/imode/deco_mail/index.html
Background images, colour, animation, animated text, ringing tone or music	Generic personalisation	describes the user's personality / mood	
Skin	Opera Mini 2.0 skin	The user can change the skin to fit her/his mood / taste / personality.	
Text	Nokia wellness diary	You can monitor and track a range of everyday well-being parameters, including weight, eating habits, exercise, blood pressure and others. Because this health journal resides on a personal mobile device, you will have privacy and ease of speedy use in everyday situations as well as the convenience of mobile data, readily available to be shared with a physician or a personal trainer.	http://www.nokia.com/A4384042
Photography	Smile Measurement Software	Measures the smile factor in a picture.	http://gizmodo.com/gadgets/smile-measurement-software/

Appendix E – Emotion recognition methods

Channel	Method	Recognition rate	Source
Facial expression	Tracking features like edges, nose, eye, brows	86 - 92%	See Cowie et al. (2001) for more details
	Model alignment using 3D mesh based on isoparametric triangular shell elements to create a dynalic model of the face. Each expression was divided into three distinct phases, i.e., application, release and relaxation	about 98%	See Cowie et al. (2001) for more details
	Static images	Difficult, with the exception of Padgett (1996) who reached a recognition rate of 86%	See Cowie et al. (2001) for more details
Speech	Tracking acoustic (pich, intensity, duration, spectral), contour, tone based, voice quality.	64 - 98%	Cowie et al., 2001; Pantic 2003 for more details
Brain	Facial electromyography (EMG)	n/a	Ravaja et. al., 2004
	Tracking with fMRI the level of Blood Oxygenation Level-Dependent (BOLD) signal in the Amygdala.	n/a	Büchel et al, 1998
Skin	Tracking Skin Galvanic Response. Fear produced a higher level of tonic arousal and larger phasic skin conductance.	n/a	Lanzetta & Orr, 1986
Eyes	Tracking eye blinks, pupil dilation, eye movements.	n/a	Ravaja et. al., 2004

Channel	Method	Recognition rate	Source
Heart rate	Heart rate acceleration was higher during fear imagery than neutral imagery or silent repetition of neutral sentences or fearful sentences.	n/a	Vrana SC, Cuthbert BN, Lang PJ, 1986
Text	Happy, neutral and unhappy emotional states are recognized using semantic labels	61.18 - 71%	Wu, Chuang, & Lin (2006)
Multiple channels	Galvanic Skin Response (GSR), heartbeat, respiration, and electrocardiogram (ECG).	81%	Picard et. al., 2001
	Tracking skin temperature, heart rate, and GSR	83%	Nasoz, Alvarez, CL Lisetti, & Finkelstein, 2004
	Using the BodyMedia SenseWear	sadness (92%), anger (88%), surprise (70%), fear (87%), frustration (82%) and amusement (83%)	Nasoz et al., 2004

Other features such as gesture, posture, conversation, music, visual art, haptic cues (pressure), product usage, health & pregancy and other people's proximity, though less effective, have also been researched in the context of emotion recognition.

Appendix F – List of mobile phone activities

Verkasalo's list of use cases gives great insight of what data can is available on the mobile phone. He describes it as a "usage activity typically includes an application launch, data session, taken photo etc. The text in the parentheses tells how the usage activity is identified." (Verkasalo, 2007, p.124)

- Outbound Voice calling (outbound voice call)
- Inbound Voice calling (inbound voice call)
- Missed voice calling (missed voice call)
- Outbound video calling (outbound video call)
- Inbound Video calling (inbound video call)
- Missed video calling (missed video call)
- Outbound SMS messaging (outbound SMS message)
- Inbound SMS messaging (inbound SMS message)
- Outbound MMS messaging (outbound MMS message)
- Inbound MMS messaging (inbound MMS message)
- Outbound email messaging (outbound email message with the platform messaging application)
- Inbound email messaging (inbound email message with the platform messaging application)
- Outbound Bluetooth messaging (outbound Bluetooth message)
- Inbound Bluetooth messaging (inbound Bluetooth message)
- Bluetooth usage (a usage action with a Bluetooth device, only for 3G devices)
- Packet data (packet data session generating at least 10 KB)
- Browsing packet data (browsing packet data session generating at least 10 KB)
- 3rd party email application data usage (3rd party email application launch generating some packet data)
- Email packet data usage (Email application launch generating some packet data)
- Streaming packet data (packet data session of a multimedia application generating at least 10 KB)
- Infotainment packet data usage (packet data session of an infot. application generating at least 10 KB)
- Internet services packet data usage (packet data session of an internet services application generating at
- least 10 KB, e.g. Yahoo, Google, Skype, MSN, AOL applications, instant messaging usage)
- P2P packet data (packet data session of a P2P application generating at least 10 KB)
- VOIP packet data (packet data session of a VOIP application generating at least 10 KB)
- Instant messaging packet data (packet data session of an IM application generating at least 2 KB)
- Radio usage (Visual Radio, FMRadio or any other radio launch lasting at least 15 seconds)
- Internet Radio usage (packet data session of Internet Radio generating at least 2 KB)
- Blogging application usage (blogging application launch lasting at least 15 seconds)
- Multimedia - Imaging/photos (imaging/photo application launch lasting at least 15 seconds)
- Multimedia - movie/video (movie/video application launch lasting at least 15 seconds)
- Multimedia - music/sounds (music/sounds application launch lasting at least 15 seconds)

- Config (configuration application launch lasting at least 15 seconds)
- Utility (utility application launch lasting at least 15 seconds)
- Productivity (productivity application launch lasting at least 15 seconds)
- PIM (pim application launch lasting at least 3 seconds)
- Infotainment (infotainment application launch lasting at least 15 seconds)
- Games (games launch lasting at least 15 seconds)
- Camera - Photo (a taken photo with camera)
- Camera - Video (a taken video with camera)
- Clock/Alarm (platform clock launch)
- Calendar usage (Calendar launch lasting at least 3 seconds)
- Calendar entry (made entry to calendar)
- Profile change (change of profile action)
- Phone turn off (phone switch off)
- Application installations (an application installation on the phone)