Studying User Behaviour Through Human-Smartphone Interactions and Experience Sampling Method Data

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To my sister, Nyala, and my parents, Ronald and Bettie,
for their patience and support.

Abstract

Nowadays, smartphones are considered ubiquitous with a large share of the global population carrying their phones everywhere and spending significant portions of their day interacting with the device. Due to the high habitual and repetitive usage and the diversity of the activities carried out through the handset, smartphones appear to be a convenient inspective tool to capture and understand human behaviour.

In this thesis, we are interested in evaluating an individual's disposition based on their smartphone usage behaviour. We achieve this through the deployment of the bespoke smartphone app *Tymer* within a cohort of 64 participants. Following ESM methodology principles, the app was designed to collect various metrics including self-reported mood and unobtrusively recorded low-level UI interaction event data for a period of 8 weeks. In contrast to commonly used alternatives such as inferring the time users spent on their phone or using self-report measures, our novel approach of quantifying smartphone usage based on the number of interaction events provides a more detailed and clearer signal.

Using this method, we assess various hypotheses relating to smartphone usage and uncover associations with Smartphone Addiction. Particular significant findings in this domain further motivate the subsequent investigation of the Snapchat app. We also find evidence for the usefulness of smartphone usage behaviours in the prediction of mood states. Our results support the idea that smartphone-human interactions are a valuable proxy for the quantification of smartphone usage behaviours, and that the smartphone is a suitable tool to infer an individual's disposition, such as their proneness to Smartphone Addiction and their mood.

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Contents

List of Publications

The work introduced in this thesis is based on the following publications.

- Beryl Noë, Liam D Turner, David E Linden, Stuart M Allen, Gregory R Maio, and Roger M Whitaker. Timing rather than user traits mediates mood sampling on smartphones. *BMC research notes*, 10(1):481, 2017.
- Beryl Noë, Liam D Turner, David E Linden, Stuart M Allen, Bjorn Winkens, and Roger M Whitaker. Identifying Indicators of Smartphone Addiction Through User-App Interaction. *Computers in Human Behavior*, 99:56-65, 2019.
- Beryl Noë, Liam D Turner, and Roger M Whitaker. Smartphone interaction and survey data as predictors of snapchat usage. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers*, pages 438-445. ACM, 2019.

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List of Acronyms

BFI Big Five Inventory [97]

CM Current Mood

DM Daily Mood

DSUQ Demographics and Smartphone Usage Questionnaire

EMA Ecological Momentary Assessment

ESM Experience Sampling Method

FoMO Fear of Missing Out

IA Internet Addiction

MCQ Monetary-Choice Questionnaire [104]

PM Percentage of Matching CM-DM pairs

PANAS Positive and Negative Affect Schedule [208]

SA Smartphone Addiction

SAS Smartphone Addiction Scale [110]

UI User Interface

Chapter 1

Introduction

The Smartphone is central to this thesis as a platform for interaction with users. Only in the last decade has the technology matured and become widespread. In this section we provide a background to the use of smartphones and their origins (Section 1.1), and outline the main implications that have arisen, concerning human cognition and well-being, specifically delving into the topic of Smartphone Addiction (Section 1.2. We furthermore highlight the major research directions of this thesis (Section 1.4) and its main contributions (Section 1.5). Finally, we give an overview of the thesis structure in Section 1.6.

1.1 Smartphone Origins and Its Ubiquity

In 2007, Apple's first iPhone marked the transition from "dumb" to "smart" mobile phones with among other things, a touchscreen, internet access, a camera, headset controls, and apps that changed the phone from being a device almost exclusively used for communication to that of a pocket computer also capable of being used for emails, navigation, and entertainment purposes. The Apple App Store and the Android Market (now known as Google Play Store) were launched just one year later, in 2008, and grew to each have an assortment of over 2 million apps in the present day. 2012 marked the arrival of the 4G network, which from then on provided much faster connectivity than the previously available networks such as 3G. In 2014, Apple launched Apple

Pay, followed in 2015 by Google Pay, which enabled users to make purchases akin of contactless card payments using the near field communication (NFC) system.

The smartphone is not only a high-end competitor to the classic non-touchscreen mobile phone, but it is also a low-end alternative to tablets and laptops being able to accomplish many tasks traditionally performed on a laptop or desktop PC (eg. sending emails, watching a TV show). Although it is restricted in screen size, processing power and storage, the smartphone retains the easy portability of the mobile phone. In less than 7 years, the worldwide market share of mobile website traffic reached that of desktop devices [177].

While it was not available on the market yet just over a decade ago, the smartphone has now become a ubiquitous device in the everyday lives of more than a third of the global population. In 2018, an estimated 5.1 billion people own mobile phones amounting to a worldwide penetration rate of 67% [82]. More than half of these users (2.9 billion) are smartphone users [182]. In advanced economies, the median smartphone penetration rate has reached 76% in 2018, going as far as 95% in South Korea [154]. Age differences account for the biggest gaps in smartphone ownership in both emerging and developed economies. For instance, 93% of British respondents aged 18-34 owned a smartphone, while this number was only 60% for the citizens over 50 [154].

These statistics indicate that smartphone usage is one of the biggest technological revolutions of the 21st century. Overall, the introduction of smartphones has been considered a positive change in many ways: it has promoted an increase in communication with friends and family, brought entertainment to downtime moments, has made users more productive through countless useful tool apps, but also more informed by an increased tendency to search for information [206, 126]. Not all has changed for the better however: the ease of access and the fast growth of smartphone usage has sparked concerns about habit formation (e.g., [146, 75]) and problematic use (e.g., [169, 199, 54, 64]).

Social norms too have been adjusted since the introduction of smartphones in social settings. Phones notably have been identified as a distraction from meaningful face-to-face interactions [57, 107, 4] and in their research studying the effects of mobile messaging during a conversation, Vanden Abeele and colleagues [200] found that a texting interaction partner was seen as less attentive. In contrast, Bayer and colleagues [20] have reported that in the sample of American undergraduate students they studied, the average closeness of an interaction partner communicating through the social app Snapchat was significantly higher than those communicating through face-to-face communication, but was not found to be different from texting and calling, even though face-to-face communication was experienced as more pleasant.

Recent years also saw the documentation of “phubbing”, the act of snubbing someone in a social setting by busying oneself on their phone. The phenomenon occurs commonly as denoted by Chotpitayasunondh and Douglas [43] who counted 31.9% of their sample being phubbed 2 or 3 times per day with 23.9% being phubbed 4 or more times. Phubbing and being phubbed was positively associated with the view of seeing phubbing as normative. Gender was also found to moderate this interaction as women were found to phub more and for longer periods of time than men, and were also phubbed more by their companions than men [43].

1.2 Smartphone Addiction

The utility combined with the availability of the smartphone have helped to fuel compulsive smartphone usage, based on engagement providing positive stimuli for the user. This has opened up the opportunity for Smartphone Addiction to take hold. In this section we describe this further.

1.2.1 Behavioural Addictions

Addiction is a complex brain disorder generally manifested by psychological and/or physical dependence and impaired control. Different type of addictions are generally categorised into substance use and non-substance use (ie. behavioural) addictions by the two main bodies concerned with classifying mental disorders, the World Health Organisation (WHO) and the American Psychological Association (APA). Behavioural addictions share many similarities to substance abuse disorders, but differ inherently in the way they are caused not by a substance with chemical properties that lead to dependence, but by a specific behaviour that is experienced as rewarding despite associated negative consequences [5]. As such, it has been argued that any stimulating experience can potentially become addictive [176]. In contrast, Kardefelt-Winther and colleagues [99] have warned against overpathologising behaviours characterised by periods of high engagement that do not lead to significant functional impairment or distress. They propose a new definition for behavioural addiction: 'A repeated behaviour leading to significant harm or distress. The behaviour is not reduced by the person and persists over a significant period of time. The harm or distress is of a functionally impairing nature.' (p. 1710) along with four exclusion criteria. These criteria are the following: '1. The behaviour is better explained by an underlying disorder (e.g. a depressive disorder or impulse-control disorder). 2. The functional impairment results from an activity that, although potentially harmful, is the consequence of a willful choice (e.g. high-level sports). 3. The behaviour can be characterized as a period of prolonged intensive involvement that detracts time and focus from other aspects of life, but does not lead to significant functional impairment or distress for the individual. 4. The behaviour is the result of a coping strategy.'

Smartphone Addiction has not yet received the clinical acknowledgement from the WHO and APA, but as of 2019, the WHO have identified two behavioural addiction disorders: gambling disorder and gaming disorder [213], while the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM) [9] lists gambling disorder as the only non-substance addictive disorder.

1.2.2 Extending Internet Addiction

Smartphone Addiction (SA) is an extension of Internet Addiction (IA) [215], which may also encompass other forms of behaviour bundled through the device, such as gaming, social networking, and online shopping [30, 138]. SA broadly refers to the condition leading to uncontrolled smartphone use despite the experience of negative repercussions on personal and social life. From an initial focus on the "cell-phone" as a means to communicate (e.g., [94, 148]), the functionality provided by the latest generation of smartphones allows untethered Internet access, with applications optimised for mobile usage.

In recent years, with the numbers for smartphone and mobile phone penetration steadily rise worldwide, research on SA has gained more traction. In an effort to create a better understanding of the phenomenon of cell-phone addiction, De-Sola Gutiérrez and colleagues [53] have reviewed an extensive amount of literature on the topic and compiled a meaningful review that looks into the definition of cell-phone addiction and into characteristics of individuals who suffer from it.

Notably, De-Sola Gutiérrez and colleagues have identified some of the defining elements of mobile phone addiction as being the following:

- excessive use, dependence, difficulty controlling use, craving, increasing use
- the need to feel connected
- feeling lost or irritable when separated from cell phone
- problematic and conscious use in dangerous or prohibited contexts
- the loss of interest in other activities
- preferring cell phone to personal contact

- stress and changes in mood due to the need to respond immediately to messages
- continuation of behaviour despite negative consequences

These issues have been used in various scales to determine smartphone addiction proneness [110, 124, 189], which are inspected more closely in Chapter 2. Research into SA has led to an considerable body of research linking SA with individual characteristics and behaviours. An overview of this is given in Section 1.2.3. For a more extensive and in depth analysis, we would like to refer to De-Sola Gutiérrez and colleagues [53]'s review paper.

1.2.3 Individual characteristics and smartphone addiction

Individual differences in users mediate their susceptibility to addiction, with particular features being significant. Research into socio-demographic factors associated with problematic mobile phone use has shown that younger individuals are at a higher risk of developing an addiction, which is thought to be linked to lesser self-control exerted by individuals at that age [26]. Particularly children who received their first phone under the age of 13 were more likely to become addicted [167]. In general, younger rather than older individuals spend more time on their phone [53], especially teenagers [179, 125]. Gender differences have also been observed with women showing higher levels of addiction than men [53]. While texting, direct voice communications and games set the male usage behaviour more apart [161, 53], women's smartphone usage has been linked to sociability with texting and instant messaging app usage being particularly prevalent. In contrast to women, men were also found to use their phone more often in dangerous situations [28].

In regards to personality and other psychological characteristics, problematic mobile use has been linked to Neuroticism, Extraversion (especially in the case of smartphone use for social reasons) [112, 53], low self-esteem [26] and loneliness [53]. In contrast, individuals unlikely to be addicted to smartphones displayed high levels of Conscientiousness and more self-control. Contradictory findings have been found in this area, which are well summarised in De-Sola Gutiérrez and colleagues' review [53].

SA has moreover been linked to specific user behaviours, namely higher or excessive usage, a higher number of phone calls and texting, higher social media activity and particularly the use Facebook, Instagram and Twitter [161, 168, 53]. This is discussed more extensively in Chapter 4.

1.3 Mood and Addiction

For both substance addictions [100] and behavioural addictions [78], mood modification is frequently listed as one of the core symptoms characteristic of addiction. Mood modifications typically refer to the experience of an arousing "high" or a numbing "low" [79]. For example, negative mood has been found to have a moderating effect on the interaction between Pathological Buying and impulsivity [143], but also occurred to a higher degree in exercise addicts rather than healthy controls after a 2-week period of exercise deprivation [13]. Both IA [216, 102, 3, 50, 3, 50] and online gaming have been associated with higher levels of depression and anxiety [210, 135], and more generally, a positive link has been found between depressive symptoms and all types of electronic media use at night time [121].

1.4 Research Direction

The strong relationship that users have with the smartphone gives a basis for using it to understand the experiences and behaviour of the individual, particularly in relation to cognitive behaviour. Accordingly, we focus our research in this direction. Measures of smartphone activity, crucial in many topics of research surrounding smartphone use, typically involve self-reporting (e.g., [63]) or recording screen time (e.g., [69]). Although valid and worthy, these approaches have limitations, such as allowing subjects to filter their own reports of behaviour [103] or including passive usage. Additionally, important details can be obfuscated that a user may consider insignificant, such as a dependency on a particular type of physical interaction with the device, or excessive repetition. Automated collection of user-data sets a new standard [175], but this is more challenging to achieve and less well-established.

These issues motivate the alternative approach to smartphone activity assessment taken in this thesis, which goes beyond monitoring high level metrics such as time on the device, to understand how the detailed interactions with the smartphone may influence mood or coincide with SA. The approach involves automatically recording all of the user's interactions with the UI for all their applications and activity. Related work taking this approach is scant [32]: although tracking device interaction is an established technique in the human-computer interaction literature [172, 96, 151, 34], detailed assessment of correlations with human dispositions such as Smartphone Addition proneness are limited, with usage typically being assessed at the higher level (e.g., time on device [67, 87]) and correlated with other aspects such as personality [38, 175] and mood [122].

This leads to the evaluation of this new data collection method and the following questions as main motivation for the thesis:

RQ1 **To what extent can smartphone interaction events be used to better represent usage behaviour in comparison to temporal features?**

RQ2 **Can smartphones be used as an unobtrusive tool to infer a user's disposition?**

1.5 Contributions

Through answering the above question, we make the following contributions:

C1 **Design of the data collection method: integration of smartphone data collection and Experience Sampling Method (ESM)**. In Chapter 2, the main research methodologies and psychometric tests used for the study design and the particularities of combining the ESM method and smartphone data collection are discussed. An overview of all data used in the subsequent chapters is also given.

C2 **Comparison of two sampling frequencies of mood for ESM data collection: discussion of advantages and disadvantages.** In Chapter 3, a comparison is made between the use of 3 momentary mood assessments (CM reports) per day vs. 1 daily assessment (DM report). A significant overlap between the two reporting frequencies is demonstrated and while individual and intrinsic characteristics such as age, gender and personality had no effect on whether at least one CM matched the DM report recorded on the same day, memory biases were found to influence which CM report matched the DM report.

C3 **Analysis of predictors of SA: identification of smartphone usage behaviours that may contribute to SA and validation of UI interaction events as useful proxy for smartphone usage behaviours.** Specifically considering active usage, the activity in 29 apps and 21 app categories is analysed alongside 5 smartphone usage behaviours in respect to SA in Chapter 4. High usage in apps from the Lifestyle and Social categories, and in particular within the app Snapchat, were found to be most associated with SA.

C4 **Analysis of predictors of Snapchat usage: identification of demographic and behavioural factors characteristic of Snapchat usage.** In Chapter 5, we examine both survey and smartphone interaction data and find age, SA score, sleep amount, wake up frequency, daily happiness and boredom, Conscientiousness score, and interactions with a few different apps to be significant predictors of Snapchat usage.

C5 **Analysis of mood predictors: identification of app interaction behaviours preceding mood states and further evidence for the value of UI interaction events as proxy for smartphone usage behaviours.** In Chapter 6, smartphone interactions preceding CM and DM reports were investigated for their impact on user mood. The usage of email apps, high overall usage and scroll behaviour were found to be predictors of negative moods, while the use of the instant messaging app WhatsApp coincided with higher arousal moods being reported.

1.6 Thesis Structure

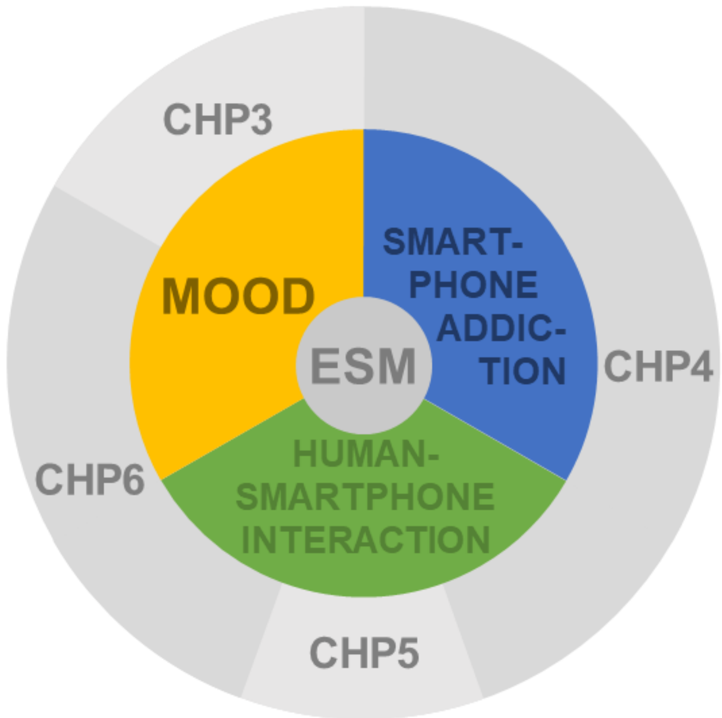


Figure 1.1: Relationship between the main chapters and the major themes of this thesis.

Aligned to the contributions in Section 1.5, this thesis follows four main themes: experience sampling on smartphones (Chapters 3, 4, 5, and 6), mood (Chapters 3 and 6), human-smartphone interaction behaviours (Chapters 4, 5, and 6), and smartphone addiction (Chapter 4). The interaction between each of these topics in all of the chapters of this thesis can be seen in Figure 1.1.

As the literature concerns a diverse range of topics, a review of existing research is presented in each chapter. In **Chapter 2, Methodology,** an overview of the ESM method is first discussed, followed by a discussion of how this study contributes to this the methodology.

The chapter then describes the data collection process which led to the dataset used throughout thesis. Most importantly, this encompasses the design of the *Tymer* app, which was used to both retrieve participants' smartphone interaction behaviours, and also prompted them to answer a set of micro-surveys on a daily basis providing longitudinal data concerning a wide range of metrics. This chapter also includes the description of the overall study design, the ethical management of the data collection, approval from the ethics board, the recruitment of the participants, and a survey of the administered psychometric surveys and their alternatives. Lastly, an overview of the data is then provided, highlighting particularly the data used in later chapters. This supports contribution C1.

In **Chapter 3, Timing in ESM,** an overview of the literature on sampling frequency is given and two alternative sampling approaches are introduced and evaluated. Multiple micro-surveys prompting the participant to report their current mood (CM reports) are juxtaposed with the results given in an evening survey (DM reports) where the participant is asked for a summary of their mood over the whole day. The influence of the order of CM reports is also evaluated with the last CM report particularly matching the DM report more frequently than previous reports. Advantages and disadvantages of alternative sampling frequencies are finally discussed. This supports contribution C2.

In **Chapter 4, User Interactions and Smartphone Addiction,** an overview of the literature on behaviours associated with problematic phone usage is presented. Participants' usage of specific popular apps and app categories is evaluated against their

SA score. Overall usage and different types of touch-interactions are also assessed. The usage of social and Lifestyle apps and the Snapchat app are found to particularly correlate with SA. This supports contribution C3.

Leading on from the findings in the previous chapter, **Chapter 5, User Interactions and Snapchat,** focuses on one particular app from the Social category: Snapchat, which is identified as having particularly interesting user-patterns of interaction. In this chapter, an overview of the literature on Snapchat is given and predictors of Snapchat usage are identified among demographic and behavioural variables, as well as variables describing sleep, mood, personality, and app interactions. The main findings include the identification of age, SA score, amount of sleep, happiness and boredom as predictors of Snapchat usage. This supports contribution C4.

In **Chapter 6, User Interactions and Mood,** an overview of the literature on the effects of different mobile phone usage behaviours on mood is given. Based on individual patterns of usage, app interaction behaviours hypothesized to influence participants' mood are evaluated. Key findings include the use of email apps and the phone in general preceding the reports of more negative moods and the use of the communication app WhatsApp being followed by mood reports rated higher in arousal. This supports contribution C5.

Finally, **Chapter 7, Discussion and Conclusion,** concludes the thesis. A summary of the main findings is given discussing all the contributions, while reviewing limitations and considering possible avenues for future work.

Chapter 2

Methodology

While the themes of each of the main chapters (3,4,5, and 6) differ a lot, resulting in background literature each discussed separately per chapter, much of the methodology of each of the studies is shared as all data considered in this thesis was collected simultaneously and no external data was used. An overview of the study design, the data collection and the data is therefore given in this chapter and referred back to in the rest of this work.

We start by discussing ESM, the research method which provides the framework for this study, and further psychometric tools which were used to collect our data. We then go on to describe how the data collection was designed and handled and give a summary of all elements of the data relevant to this thesis.

2.1 Experience Sampling Method (ESM)

ESM, also known as Ecological Momentary Assessment (EMA), is a research method first described in 1983 by Larson and Csikszentmihalyi [113] designed for the collection of self-reports describing personal experiences at multiple intervals throughout a day for a set amount of days.

The sampling event is typically triggered by a signal (also referred to as "beep") which prompts the participant to fill a survey with a set amount of closed and/or open-ended questions, but can also occur after the participant displays a specific behaviour (e.g., having a meal) or is exposed to a specific event (e.g., talking to strangers). Further tasks can be asked at sampling events, such as requesting that participants take a picture, record a few seconds of their environment in a video, or share their location with the help of their smartphone [27, 111]. Supplementary data can be collected implicitly, such as heart rate or physical activity [59] through the use of devices such as smartwatches and smartphones.

Sampling frequency may vary from once (e.g., [145]) to 10 or more times per day (e.g., [105]) and the sampling period may vary from a few days (e.g., [47]), to weeks (e.g., [173]), or even years (e.g., [81, 36]). In order to maintain participant motivation and compliance, Conner and colleagues [45] recommend to keep the number of reports to 6 or less for long sampling periods of 3 or more weeks, unless reports take less than 2 minutes.

A further consideration is the disruptiveness of sampling due to the potentially high number of interruptions and long sampling duration. ESM studies may be perceived as intrusive by participants and respondent fatigue may contribute to increasing non compliance and needs to be taken into account into the study design of ESM studies.

These considerations have been factored into the study design and have been summarised in Section 2.2.2.

2.2 Study Design

Seventy-six participants were recruited through posters, flyers and online advertisement at Cardiff University, UK in 2016. The participants were aged between 19 and 46 (M = 24.94, SD = 5.69). Thirty-nine participants were male, 36 female and 1 participant chose not to disclose their gender. Participants were selected on two aspects: they needed to have a smartphone running Android 4.4 (KitKat) or higher, and they had to have no history of mental illness. This is in conformance with Kardefelt-Winther and colleagues' exclusion criteria [99], listed earlier in Section 1.2.1. The study was approved by the ethics committee of the School of Psychology, Cardiff University. All participants provided written, informed consent.

All participants attended a briefing session where they downloaded the bespoke application *Tymer*, were given explanations about how to use the app and the distinctions between different moods and intensities they would have to report (see Appendix A.1.1), and were asked to complete four psychometric surveys (SAS [110], Positive and Negative Affect Schedule [208] (PANAS)-X [208], BFI [97], and MCQ [104]), along with a demographics questionnaire that also included some questions about general smartphone use. After 8 weeks of using *Tymer*, participants returned for a debriefing session where they completed the same set of surveys and received monetary compensation of £50.

2.2.1 Survey Data Collection

A sample of 5 surveys were administered to participants during the initial briefing and final debriefing sessions that framed the smartphone data collection period of 8 weeks. Although not all of the collected data was used in the primary analyses reported in this thesis, each of these surveys is included and discussed in the following section to provide a complete overview of the study.

Smartphone Addiction Scale (SAS)

The SAS is a 33-item self-report questionnaire developed by Kwon and colleagues in 2013 [110] to measure SA. Each item is scored on a Likert-scale from 1 ‘Strongly disagree’ to 6 ‘Strongly agree’, allowing for a range of scores between 33 and 198. The researchers subsequently also published a short version of the same survey, SAS-SV [109], which included 11 of the initial 33 questions, and for which a cut-off value of 31 for males and 33 for females was proposed to determine addiction.

Many more surveys exist to measure the impact of SA, a few well-used ones include: the Smartphone Addiction Inventory [124], the Mobile Phone Problem Usage Scale (MPPUS) [26], the Problematic Mobile Phone Use Questionnaire (PMPUQ) [28], the Mobile Phone Involvement Questionnaire (MPIQ) [203], the Mobile Phone Addiction Scale (MPAS) [89], and the Problematic Use of Mobile Phones (PUMP) [136]. An overview of these tests, and more, has been collated by De-Sola Gutiérrez and colleagues [53].

As a well-used and validated test and comparatively, one of the scales with the highest internal validity (α = 0.97), the SAS was chosen to measure SA in this work.

Expanded form of the Positive and Negative Affect Schedule (PANAS)

The PANAS-X is the expanded version of the PANAS mood self-report survey developed by Watson and Clark in 1994 [208]. The questionnaire is composed of 60 items constructed around a number of subscales: 2 general dimensions scales (positive affect and negative affect), 4 basic negative emotion scales (fear, hostility, guilt, and sadness), 3 positive emotion scales (joviality, self-assurance, and attentiveness), and 4 other affective states (shyness, fatigue, serenity, and surprise).

Many well-used and validated alternative mood surveys exist, including the Profile of Mood States (POMS) [134], a 65-item questionnaire that gives a Total Mood Disturbance score calculated from the subscales Tension, Depression, Anger, Fatigue, Confusion, and Vigour and the Brief Mood Introspection Scale (BMIS) [132], which focuses on measuring meta-moods, the thoughts and feelings an individual might have about the mood they're experiencing.

The PANAS was chosen for its bipolar composition, providing scores for both negative and positive affect, mirroring more closely the circumplex model chosen as basis for the mood survey within the *Tymer* app.

Although it was part of the data collected, responses for the PANAS questionnaire have not been used in the studies incorporated in this thesis, but may considered in a wider research study.

Big Five Inventory (BFI)

The BFI is a self-report survey developed by John and Srivastava [97] in 1999 to measure personality traits following the Five Factor model of personality [76]. These five factors (Openness to Experience, Conscientiousness, Extraversion, and Neuroticism) provide 5 dimensions according to which an individual's personality can be described. These dimensions are the following:

1. **Openness to Experience** - Unopenness to Experience: Open individuals are characterised by their curiosity, innovativity and willingness to try new things, while unopen individuals show more consistency and aversion against change. Openness to Experience is measured with some of the following descriptors: “Is original, comes up with new ideas”, “Is curious about many different things”, “Likes to reflect, play with ideas”.

2. **Conscientiousness** - Unconscientiousness: Conscientious individuals typically show higher levels of efficiency and organisation, while unconscientious individuals display more carelessness and a higher lack of focus. Conscientiousness is measured using some of the following terms: “Does a thorough job”, “Is a reliable worker”, “Makes plans and follows through with them”.

3. **Extraversion** - Introversion: Extraversion describes to what extent an individual is outgoing and sociable. In contrast, introverts display lower levels of social engagement and value and/or need more alone time. Introversion is not analogous to shyness, which is defined by the lack of comfort around other people. Extraversion is measured with some of the following items: “Is talkative”, “Generates a lot of enthusiasm”, “Has an assertive personality”.

4. **Agreeableness** - Disagreeableness: Agreeable individuals are considered friendly and compassionate, while disagreeable individuals are described as more selfish and detached. Extraversion is measured with some of the following descriptors: “Has a forgiving nature”, “Is generally trusting”, “Likes to cooperate with others”.

5. **Neuroticism** - Emotional Stability: Neurotic individuals are generally more nervous and tend to worry more. Emotional stable individuals tend to be more confident and to have more control over their emotions. Neuroticism is measured using some of the following terms: “Can be tense”, “Worries a lot”, “Gets nervous easily”.

Other personality structure models exist with HEXACO [16] being the most popular alternative to the Five Factor model. HEXACO is comprised of 6 dimensions: Honesty-Humility, Emotionality, Extraversion, Agreeableness, Conscientiousness, and Openness to experience.

For this work, the BFI questionnaire was chosen over a survey based on the Six Factor model as the use of the Five Factor model outweighs the usage of other models, with only one of the papers cited in thesis making use the HEXACO model concurrently with the Big Five model [90].

Monetary-Choice Questionnaire (MCQ)

The MCQ is a self-report survey developed by Kirby and colleagues [104] to measure impulsivity in heroin and cocaine abusers. The short survey of 27 questions asks respondents repeatedly whether they would prefer to receive a specific amount of money “today” over a slightly or significantly larger amount in a specified number of days. Answers to all 27 items serve to calculate a respondents Discounting Rate, which can be used a a proxy score for impulsivity.

Examples of questions in this survey are: “Would you prefer $54 today, or $55 in 117 days?”, “Would you prefer $15 today, or $35 in 13 days?”, “Would you prefer $69 today, or $85 in 91 days?”. It is worth noting that the use of hypothetical rewards in delay discounting tasks have reportedly resulted in similar choices as to when real rewards are employed [114].

Demographics and Smartphone Usage Questionnaire (DSUQ)

Lastly, a questionnaire was included to collect complimentary information about participants that may be relevant to the studies undertaken with the other data collected for this project. Questions included in the survey were about:

1. Demographics (e.g., age, sex, ethnicity)
2. Employment and education (e.g., employment status, highest degree earned)
3. Smartphone use (e.g., smartphone location while sleeping, top used apps)

The full questionnaire can be found in Appendix A.1.2.

2.2.2 Smartphone Data Collection: *Tymer*

Only the design of the app is discussed in this section as the development is a matter of software engineering not relevant to the thesis at hand. The *Tymer* app was designed to serve as data collection too in two ways:

1. Collection of survey data that requires participants to repetitively interact with the app’s interface
2. Collection of smartphone usage data that happens in the background and that does not require the participant’s involvement beyond consenting to the collection and pausing/restarting this if needed.

Tymer: Survey Data Collection

On a daily basis and for a period of 8 weeks, participants were prompted by notifications on their phone to complete 3 different surveys on a daily basis:

- Morning survey
- Evening survey
- Current Mood survey

All types of reports could also be completed through the application interface with a limit of 1 per day for both Morning and Evening surveys and no restrictions for the Current Mood survey.

A typical day using the *Tymer* application is depicted in Figure 2.1.

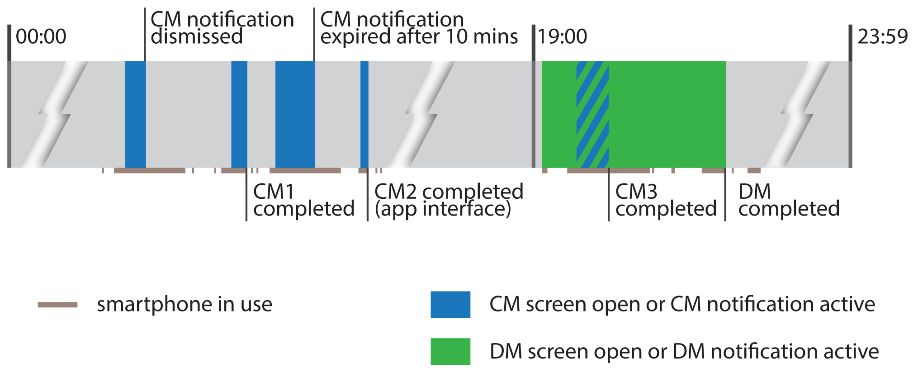


Figure 2.1: Example of a day using the *Tymer* app.

Morning Survey

When the participants used their smartphone for the first time of the day after 06:00 (local time), a notification prompted them to fill in the Morning survey. This survey aimed to capture late-evening/night lifestyle choices and experiences of the previous day. A total of 3 questions were asked:

1. How many hours did you sleep last night? (0, <3, 4-6, 7-9, 9+)
2. In comparison to your usual sleep quality, how was your sleep quality last night? (worse, same, better, N/A)
3. How many units of alcohol did you consume yesterday? (0, 1, 2-3, 4-5, 6+)

The notification and possibility to fill in the Morning survey expired at 19:00 with the arrival of the Evening survey.

Evening Survey

Every day, after 19:00, a notification prompted participants to answer the Evening survey (see Figure 2.2 (right)), which aimed to capture participants' morning and afternoon lifestyle choices and experiences. The Evening survey was normally comprised of 2 questions:

1. How long have you used your smartphone in the last 24 hours? (<1, 1-2, 2-3, 3-5, 6+)
2. On reflection, what has your mood been so far today? (Tense, Excited, Happy, Relaxed, Calm, Bored, Upset, Stressed, Neutral)

but additionally asked participants whether whether they enjoyed answering the *Tymer* surveys and could respond on a 5-point Likert scale ranging from "not at all" to "very much". The notification and possibility to fill in the Evening survey expired at 23:55.

The response to the second question will from here on be described as participants' daily mood (DM) report.

Current Mood Survey

The *Tymer* application prompted participants to report their CM using a dartboard-shaped interface (as shown in Figure 2.2 (left)), up to three times per day. In contrast to the Morning and Evening multiple choice surveys, a graphical interface was chosen for

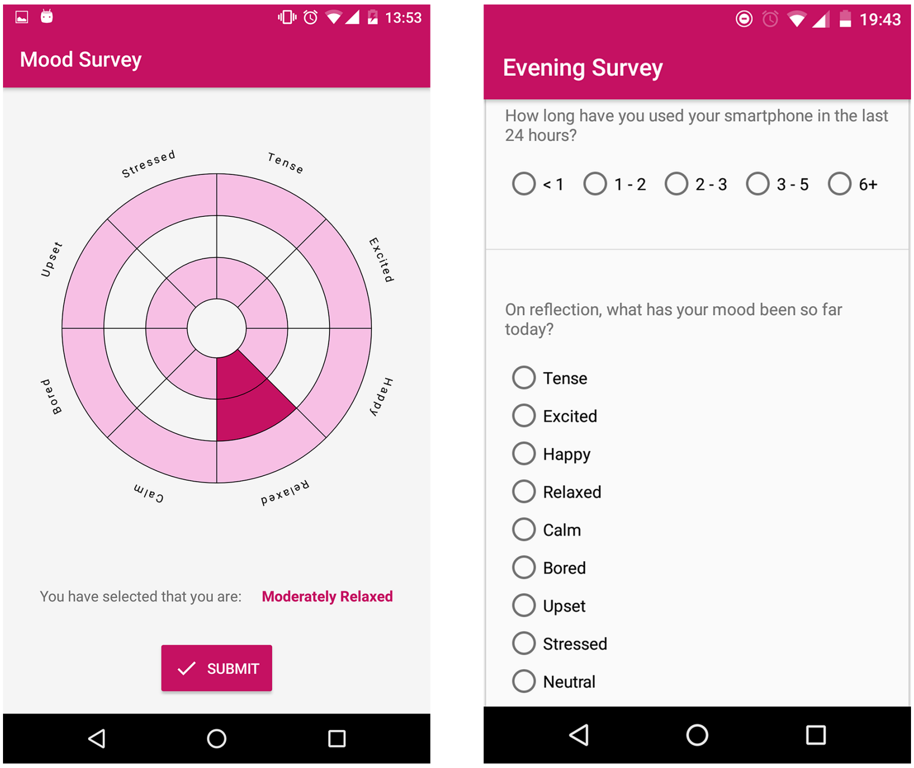


Figure 2.2: Screenshots of the CM (*left*) and DM (*right*) surveys in *Tymer*. In these examples, the user has selected their current mood to be "moderately relaxed" and has not yet chosen a daily mood.

participants to mark their current mood. The dartboard shape and location of all moods within it reflects the position of these in the Circumplex Model of Affect [164] as dictated by the moods' valence and arousal measures. The interface was introduced and explained to the participants during the briefing session (see A.1.1) using a simplified graphic of the Circumplex Model of Affect [164]. This helps the user by promoting *recognition rather than recall*, one of Nielsen's usability heuristics [144], aimed at minimising the cognitive load by giving the user a clear set of options, that are placed where they are expected. Several more usability heuristics were additionally taken into account for the design of this interface. Firstly, the selection of the mood and its intensity is clearly indicated by a darker shade in the octant of the corresponding mood and is also displayed in bolded text of the same colour beneath it. This is in accordance to the *visibility of system status* principle which supports giving the user appropriate feedback of what is happening. Furthermore and with respect to the *user control and freedom*, but also the *error prevention* principles, the user can take their time changing their mood and mood intensity selection by selecting another area of the dartboard before submitting their choice. The "submit" button is situated at the bottom of the screen (as expected based on modern *consistency and standards* principles), away from the dartboard interface to minimise misclicks. This also signifies that the user only needs 3 clicks to bring up the screen from the notification, select their current mood and mood intensity, and then submit their response, which is supportive of the *flexibility and efficiency of use* heuristic. Lastly, an *aesthetic and minimalist design* was chosen with the whole survey fitting on one screen. This further helped promote the efficient use of the interface and allowed the user to respond to the surveys one-handedly.

Participants could chose between 8 moods:

1. Tense
2. Excited
3. Happy
4. Relaxed
5. Calm
6. Bored
7. Upset
8. Stressed

with 3 levels of intensity:

1. Lightly
2. Moderately

3. Strongly
4. Neutral.

Notifications requesting the user to complete CM reports were scheduled to arrive only while the smartphone was in use and notification expiration time was set to 10 minutes.

Tymer: Smartphone Usage Data Collection

Participants were asked to use *Tymer* for 8 weeks (56 days) between their briefing and debriefing sessions. During this time, participants natural smartphone usage behaviour was collected in the background. To achieve this, it was important for *Tymer* to be installed on the participants' own phones. While this constricted the participant pool as *Tymer* could only be used Android devices and had consequences for the generalisability of our results (see Section 7.2.4), it allowed for a natural data collection setting as opposed to what could have been achieved with a study-specific device which changes the participants' day-to-day activities [198].

The data collection was mostly composed of the logging of the occurrence of specific *events*. The types of events logged included, but were not limited to: boot, power off, screen on, screen off, screen unlock, power low, window state change, tap, long tap, scroll, text selection, writing.

In this thesis however, only UI interaction events are considered, excluding events that could be ambiguous (i.e., triggered by either the user or the smartphone, such as a screen off event, that can be caused by the user switching off the screen but also by the smartphone timing out the display). This is done to avoid including smartphone generated events as they do not constitute a real UI interaction, but also to exclude passive usage (e.g., streaming a video, using the phone as a navigation system) which can count towards screen time, but does not constitute active interaction with the smartphone. The specific types of events considered are: tap, long tap, writing (e.g., striking the keyboard), scroll, and text selection (i.e., highlighting). We subsequently refer to the sum of all of these events together as “overall smartphone use”.

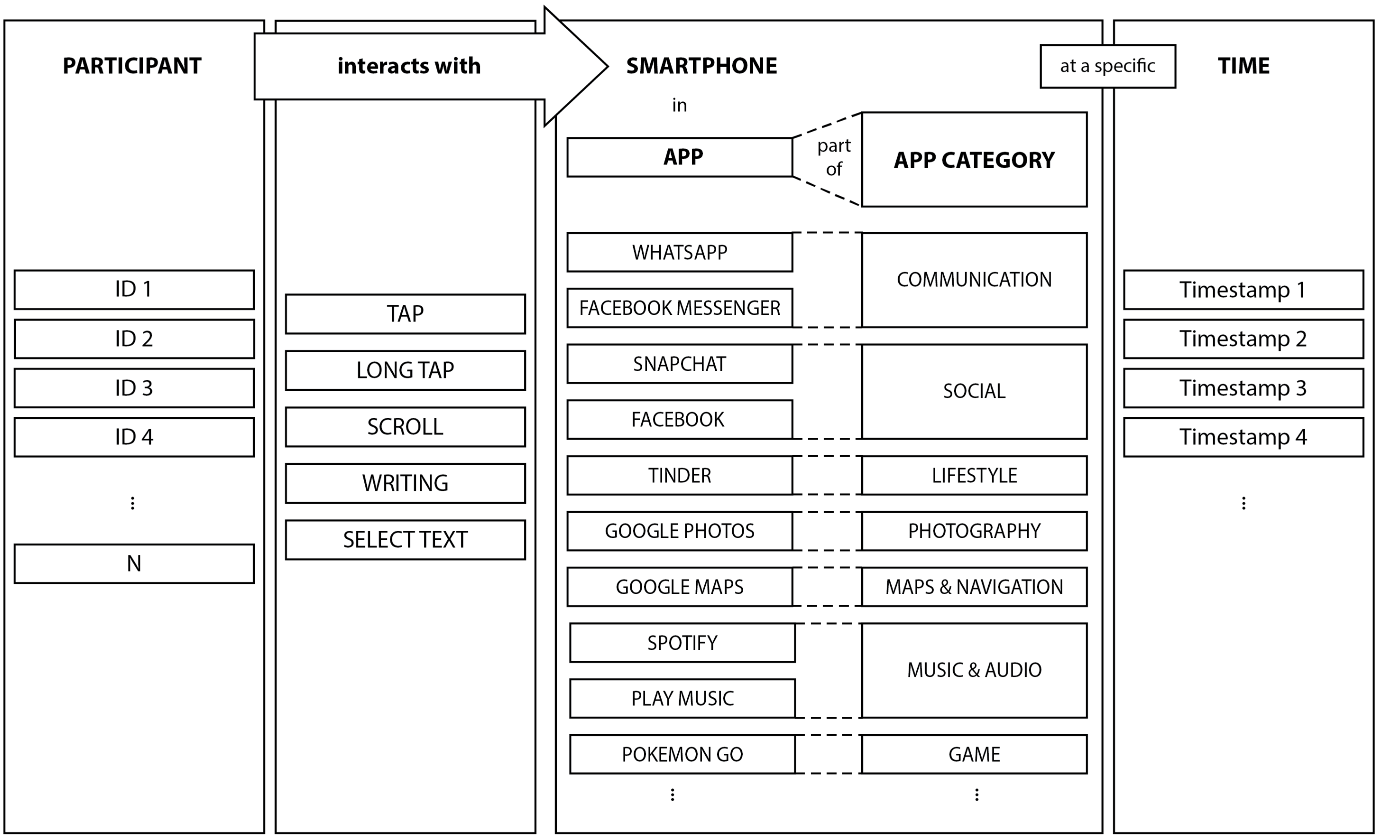


Figure 2.3: Overview of data obtained through participants interacting with apps.

Interaction events were recorded by logging the type of event (e.g., a tap), the timestamp (i.e., time and date), and the source of the event (i.e., the app with which the user interacts with, e.g., WhatsApp). An overview of the relationship between these different variables is given in Figure 2.3. Only smartphone interaction events (tap, long tap, writing, scroll, and text selection) for popular apps that at least half of the participants had used at least once were evaluated in this thesis. The number of interaction events was used as a measure of usage rather than time spent on a certain app to consider active usage only (as opposed to passive usage where the user might not be interacting with their phone e.g., while listening to music or viewing content on Netflix). This is in contrast with previous literature relying on session duration (e.g., [67, 87, 163]) or self-reported measures (e.g., [117, 56]). To the best of our knowledge, this is the first study considering this approach and considering smartphone usage at such a granular level.

Due to privacy concerns, no data deemed too personal (e.g., content of received or sent messages, search history, GPS location, etc.) was collected.

Study Design Choices to Maximise Respondent Compliance ESM Sampling

- *Tymer* was designed to be installed on participants' own phone. This is preferable to the use of a study-specific device, which is more likely to be forgotten and increases learning effects [198].
- No more than 5 sampling events per day, in accordance to Conner and colleagues' recommendations [45].
- Questionnaires were kept to a maximum of 3 questions that could be answered in under 2 minutes.
- Beeps/notifications were only issued when participants were judged to be interruptible, as determined by research on interruptibility [191, 193].
- Notifications for CM surveys, the most frequent type of survey, were scheduled to arrive at a random point of time while the smartphone had been in use for at least 1 minute. This was done to maximise the chance of the user to be interruptible without making the arrival of notifications predictable [193, 1].
- Notifications for CM surveys auto-deleted themselves after 10 minutes if the participant did not interact with the notification (timestamps for these events were however still recorded). This is in line with ESM methodology recommendations to configure prompts to answer surveys to expire after a set time [198].
- The graphical interface of the CM survey, based on the Circumplex Model of Affect [164], was designed to be intuitive and easy to use with participants only

requiring to tap the screen once to select both their current mood and the intensity of their mood.

2.3 Overview of the Data

While 76 participants were recruited and completed the surveys at the briefing and debriefing sessions, data from only 64 participants could be collected through the smartphone. The exact reason behind the lack of data for 13 participants is difficult to ascertain, but can range from voluntary abstention, change of phones, or software and hardware problems.

In this section, an overview of the data of these 64 participants will be given. It is to be noted that $N = 64$ is used for Chapters 3, 4, and 5, however differing exclusion criteria lead to the removal of more participants for both studies undertaken in Chapter 6 for which $N = 51$ and $N = 61$ is used.

2.3.1 Survey Data

Demographics Data

An overview of the participant sample is given in Table 2.1.

Table 2.1: Demographic characteristics of the sample (N = 64).

Variables	Statistics	
Age	**M**	**SD**
Years	25.4	5.87
Gender	**N**	**%**
Male	34	53.13
Female	30	46.88

Table 2.1: Demographic characteristics of the sample (N = 64).

Variables	Statistics	
Employment	**N**	**%**
Student	38	59.38
Student & employed	13	20.31
Employed	12	18.75
Unemployed	1	1.56
Education	**N**	**%**
High school, no diploma	1	1.56
High school diploma or equivalent	5	7.81
Trade / vocational training	1	1.56
Some undergraduate, no degree	14	21.88
Bachelor‘s degree	19	29.69
Master‘s degree	21	32.81
Doctorate	2	3.13
No answer	1	1.56

Smartphone Use

An overview of self-reported smartphone usage characteristics is given in Table 2.2, while a list of apps and smartphone features which participants considered to be their most used apps is given in Table 2.3.

Table 2.2: Smartphone usage characteristics of sample at briefing (N = 64).

Variables	Statistics	
Handedness	**N**	**%**
Right-handed	58	90.62
Left-handed	5	7.81
No answer	1	1.56

Table 2.2: Smartphone usage characteristics of sample at briefing (N = 64).

Variables	Statistics	
Smartphone used with	**N**	**%**
Right hand	23	35.94
Left hand	3	4.69
Both hands	37	57.81
No answer	1	1.56
Perceived usage	**N**	**%**
Below average	8	12.50
Average	41	64.06
Above average	14	21.88
No answer	1	1.56
Handedness	**N**	**%**
Right-handed	58	90.62
Left-handed	5	7.81
No answer	1	1.56
Smartphone used with	**N**	**%**
Right hand	23	35.94
Left hand	3	4.69
Both hands	37	57.81
No answer	1	1.56

Table 2.3: Number of mentions of apps and smartphone features considered to be part of the 5 most used apps or features (N = 64).

App or smartphone feature	**N**	**%**
WhatsApp	43	67.19
Facebook	41	64.06
Browser	31	48.44

Table 2.3: Number of mentions of apps and smartphone features considered to be part of the 5 most used apps or features (N = 64).

App or smartphone feature	N	%
Email (Gmail, Outlook, unspecified)	18	28.13
Instagram	17	26.56
Facebook Messenger	16	25
Snapchat	15	23.44
Game	11	17.19
Messaging	11	17.19
YouTube	10	15.63
Calendar (Google Calendar, S Planner)	8	12.5
News (BBC, The Daily Mirror, Buzzfeed)	7	10.94
Twitter	7	10.94
Camera	6	9.38
Music (Spotify, Google Play Music, unspecified)	6	9.38
Skype	5	7.81
Clock	4	6.25
Google Maps	4	6.25
Note keeping (ColorNote, Everynote, Google Keep, S Note)	4	6.25
Picture viewer or editor (Pinterest, Funny Pics, Imgur)	4	6.25
Work out (MyFitnessPal, Up)	4	6.25
Football (Football mania, PESCM, unspecified)	3	4.69
Other social (Google+, HKGolden, Weibo)	3	4.69
Phone	3	4.69
Reddit	3	4.69
Shopping (Ebay, Etsy)	7	10.94
Weather (Met Office, Weather, unspecified)	3	4.69
Other communication (Viber, WeChat)	2	3.13

Table 2.3: Number of mentions of apps and smartphone features considered to be part of the 5 most used apps or features (N = 64).

App or smartphone feature	N	%
Other	13	20.31

Smartphone Addiction Scale (SAS)

Table 2.4 shows the mean and standard deviations for the briefing (used in Chapter 5, debriefing, and the mean score calculated from the briefing and debriefing data (used in Chapter 4). The number of individuals prone to SA is also given, obtained by using the threshold suggested by Kwon and colleagues for the short version of the SAS [109].

Table 2.4: Summary of the SAS scores at briefing, debriefing, and mean of briefing and debriefing scores (N = 64).

	Briefing		Debriefing		Mean	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
SAS	89.39	23.42	86.48	19.31	88.15	20.28
	N	**%**	**N**	**%**	**N**	**%**
Addicted [109]	13	20.31	10	15.63	12	18.75

Big Five Inventory (BFI)

The BFI was mistakenly done twice by one participant at the briefing session. Only the first completed BFI was taken into account for the analysis. An overview of the Big Five trait scores of the sample is given in Table 2.5.

Table 2.5: Summary of the BFI scores at briefing and debriefing (N = 64).

	Briefing		Debriefing	
	Mean	SD	Mean	SD
Openness to Experience	3.46	.55	2.74	.70
Conscientiousness	3.71	.59	3.26	.81
Extraversion	3.25	.75	3.40	.56
Agreeableness	3.86	.61	3.53	.59
Neuroticism	2.65	.70	3.85	.60

Monetary-Choice Questionnaire (MCQ)

Table 2.6 shows the overview of the results from the MCQ survey. Two participants did not fill out the MCQ at debriefing.

Table 2.6: Summary of the MCQ scores at briefing (N = 64) and debriefing (N = 62).

	Briefing		Debriefing	
	Mean	SD	Mean	SD
k	.0156	0.0357	0.0113	0.0154

2.3.2 Mood Data

8666 completed CM surveys were collected, alongside 3266 completed DM surveys. The number of completed and uncompleted (expired, abandoned, dismissed or left blank) reports are shown for both types of surveys in Table 2.7. Table 2.8 shows an overview of the mean occurrence of each mood for both CM and DM reports.

Table 2.7: Frequencies of completion and source of CM and DM surveys (N = 64).

		CM		DM	
		count	%	count	%
all		14151	100	4116	100
source	notification	13355	94.37	3851	93.56
	app interface	796	5.63	265	6.44
completion	expired	4445	31.41	154	3.74
	abandoned	59	0.42	178	4.32
	completed	8666	61.24	3266	79.35
	dismissed	981	6.93	518	12.59
	blank	1	0.01	0	0

Table 2.8: Mean percentage of reported moods for CM and DM surveys across all participants (N = 64).

	CM		DM	
	mean	SD	mean	SD
Tense	8.07	5.64	6.07	6.80
Excited	6.16	5.08	6.69	8.58
Happy	17.56	11.27	25.84	16.84
Relaxed	23.08	13.57	23.38	16.71
Calm	15.69	10.43	11.24	9.00
Bored	7.72	8.30	8.32	11.91
Upset	4.95	3.70	3.40	3.88
Stressed	8.73	6.74	2.29	7.89
Neutral	8.02	11.68	7.77	15.05

2.3.3 Smartphone Usage Data

Participants used *Tymer* for a mean number of 55.36 days (SD = 17.80), going beyond the debriefing session in some cases (see Figure 2.4).

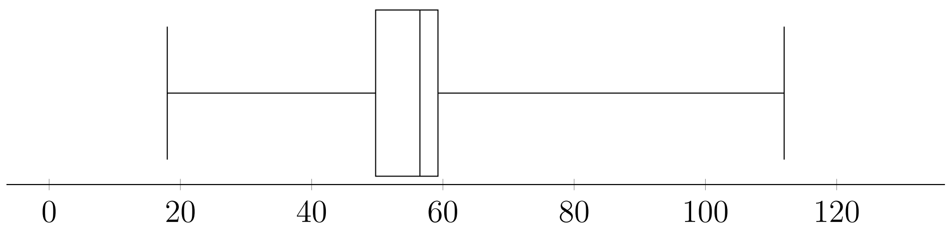


Figure 2.4: Number of distinct days *Tymer* active on participants' phones (N = 64).

We note that a large numbers of events were recorded over the period (see Figure 2.5), with scrolling making a particularly significant contribution.

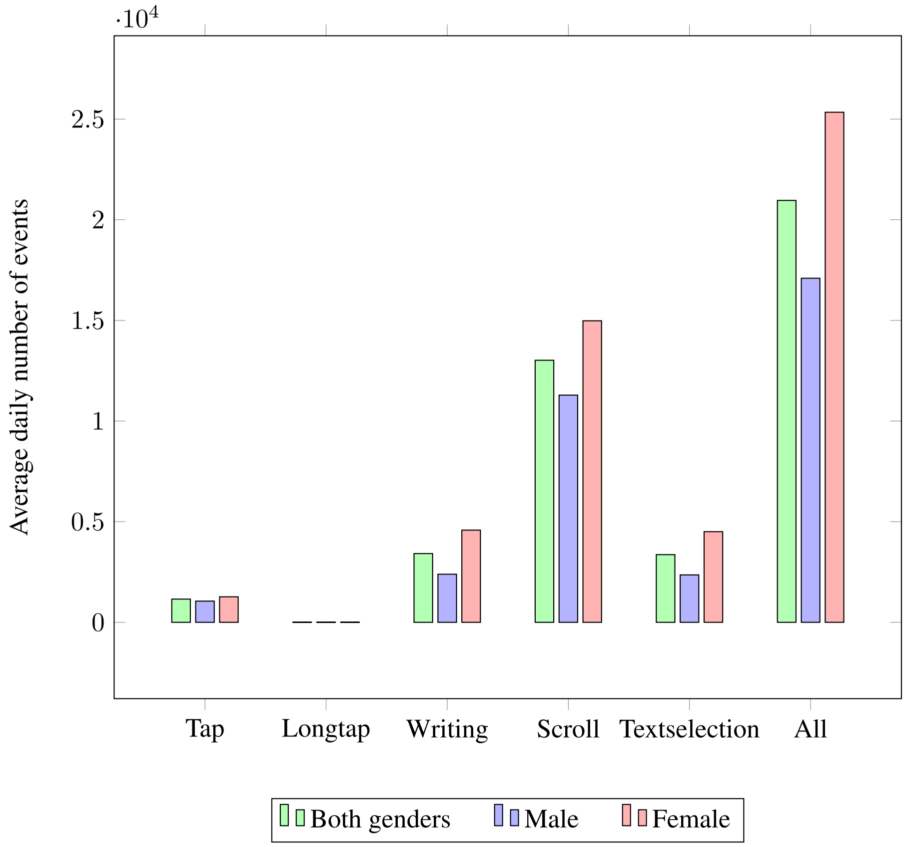


Figure 2.5: Average number of daily events per event type and gender.

2.3.4 Overview of All Data Used in this Thesis

Table 2.9 gives an overview of which type of data was used in each of the main Chapters in this thesis.

Table 2.9: Overview of Chapters in which survey and smartphone usage data are used.

Type of data	Chapters
Demographics	
gender	3-6
age	3-6
Survey	
SA score (SAS)	3-5
Personality scores (BFI)	3, 5
Impulsivity score (MCQ)	3, 5
Mood	
CM	3, 6
DM	3, 5, 6
Smartphone usage (interaction events)	
overall usage	4, 6
popular app categories	4, 6
popular apps	4, 5, 6

2.4 Conclusion

In summary, we collected a large range of data based on a study design built on top of well-established research methodology and key psychometric tests, which will support the investigation of mood sampling frequency in Chapter 3, SA in Chapter 4, and app usage in concurrence with participant affect in Chapters 5 and 6.

This chapter constitutes the following contribution (see Section 1.5) to this thesis:

C1 Design of the data collection method: integration of smartphone data collection and ESM.

Chapter 3

Timing in ESM

Parts of this chapter have been published in the peer-reviewed journal BMC Research Notes:

Beryl Noë, Liam D Turner, David E Linden, Stuart M Allen, Gregory R Maio, and Roger M Whitaker. Timing rather than user traits mediates mood sampling on smartphones. *BMC research notes*, 10(1):481, 2017.

Sampling frequency is a fundamental variable in ESM studies and choosing how many times a questionnaire should be administered for a specific time period is one of the first study design choices one needs to address. In this chapter, we address this question in the context of mood sampling. Affective states are usually either collected by asking the participant for their current mood or for a recollection of their mood states over a specific period of time (e.g. a day). We investigate the presence of any effects that explain differences between current and daily reported moods and outline design recommendations for mood sampling using smartphones.

3.1 Introduction

ESM data collection typically involves repetitively sampling participant moods along with other measures (see Section 2.1) over several days. Sampling the mood of participants in this way requires a design choice to be made: principally either sampling current moods several times per day versus collecting mood only once daily. This choice has different implications for the participant. A single mood report requires the participant to be accurate with their reflection of the whole day, whereas current mood reporting samples a participant's mood at a particular time, but requires more frequent interruption of the user. As such, individual differences between participants could influence responses to the alternative methods of collection. Therefore we investigate whether these two methods are interchangeable and whether factors exist to explain any differences between them.

3.1.1 Investigated Factors

Diverse factors could have an effect on how participants respond to survey fill-out prompts on their phone. In this section, we discuss possible individual characteristics of interest in respect to smartphones, the medium investigated in this study, and survey response behaviour.

Intrinsic Characteristics

Individual differences may result in alternative response dispositions towards surveys [68, 127, 162, 195, 74]. Work in this area has found associations with Big Five personality traits but also need for cognition, a trait that refers to people's tendency to engage in, and enjoy effortful cognitive activity [33]. Indeed, individuals with higher scores in the Conscientiousness, Agreeableness and Open to Experience traits are more likely to participate in a survey, while individuals with a higher need for cognition are more likely to log in to a web survey but less likely to finish it. Individuals with higher Emotional Stability however are more likely to complete the survey once they've logged in. Age, gender and education level too have been determined to have an effect on survey response rates with women [174, 49, 140], younger [140], and more educated people [49] being more likely to participate in surveys. While these findings were collected from paper based or online surveys, participants might be differently inclined to smartphone-based surveys. Indeed, smartphone interruption to gain user attention and response is an emerging and already a complex field on its own [191].

Certain personality facets could also influence response to the alternative approaches to surveying mood. In particular, Conscientiousness could account for a higher degree of overlap between currently reported mood and daily reported mood, as it is associated with higher individual integrity and honesty [142]. In contrast, the lack of premeditation might cause more impulsive individuals to not reflect fully on the moods they have felt during the day resulting in less overlap between current and daily reported moods [212].

The ESM methodology has relatively recently migrated to the smartphone (e.g., [159, 55]), individual characteristics related to smartphone usage may therefore be of interest as differences in smartphone usage might introduce differences in how participants complete smartphone-based surveys. In particular, SA is a recognised phenomenon [110] that could contribute to a mismatch in the reporting of currently and daily reported mood states. We might expect addicted individuals to report more negative moods overall (i.e. as a daily mood report), but also report more positive mood states specifically during periods of smartphone usage. Indeed, Internet and computer use is associated with a pleasant experience that distracts users from negative moods, which may have caused the user to turn to the Internet or computer in the first place [29, 44]. The smartphone use in itself is therefore rewarded and reinforced by the positive experience of an arousing “high” or a tranquilising “numbing”.

Mood Report Characteristics

Lastly, it is also important to note that the intensity of currently reported mood states and the amount of time between current and daily mood reports might have moderating effects. Indeed, it is to be expected that the current mood reported closest in time to the daily mood is more likely to match the latter. This effect can be predicted based on memory biases such as the recency effect [141]. The first reported current mood too is more likely to match the daily mood according to the primacy effect [141]. Similarly, the Peak-end rule [73] would suggest that the higher the intensity of the current reported mood is, the more likely the daily mood is to be the same. Finally, the valence of the experienced moods may play a moderating role too. Indeed the Fading Affect Bias describes the phenomenon in which the intensity of negative affect fades faster than the intensity of positive affect in memories [202]. Positive current mood reports may therefore match daily moods more frequently.

3.2 Methods

Data analysed in this chapter was collected through the *Tymer* application and through surveys held during the briefing session. How this data was collected is described in more detail in Section 2.2.

We use the following data sources in this chapter:

- Demographics data: gender, age
- Survey data (briefing and debriefing):
  - BFI scores
  - MCQ score
  - SAS score
- Mood data: CM, DM

3.2.1 Data Cleaning

As explained in Section 2.3, the data from 64 participants was used in this chapter.

Pairs of CM and DM surveys undertaken on the same day were analysed (where one day was defined as going from 00:00:00 to 23:59:59 in the time-zone that the participant was in). In case several DM surveys were completed for one day, only the first one was considered. A comparison of the dataset should instead the last DM have been used is shown in Table 3.1.

Table 3.1: Implications of keeping the first or last DM when more than one DM was completed per day.

	all data	keep first DM	keep last DM
nbr of unique DM	3048	2667	2667
nbr of CM-DM pairs	9848	7893	7893
nbr of CM-DM matches	2959 (30.0%)	2529 (32.0%)	2464 (31.2%)
nbr of DM with at least one CM match	2168 (71.1%)	1835 (68.8%)	1795 (67.3%)

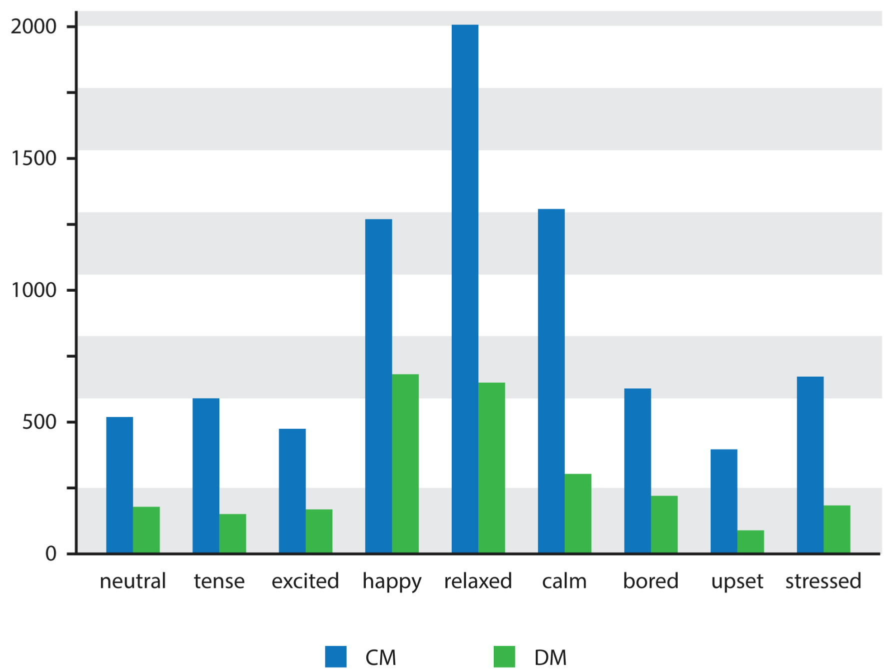


Figure 3.1: Count of reported moods for CM and DM surveys.

Days without at least both one DM and one CM survey were not considered. This resulted in 7893 unique CM surveys and 2667 unique DM surveys being analysed,

Figure 3.2: Percentages of reported moods for CM and DM surveys.

resulting together in 9848 pairs of current and daily mood surveys. Figures 3.1 and 3.2 show the number of reported mood states for both CM and DM surveys. Table 3.2 lists the frequencies of the different reported intensities for CM reports.

Table 3.2: Frequencies of intensities reported for CM reports.

intensity	count	percentage
neutral	523	6.63
slightly	3252	41.20
moderately	3144	39.83
strongly	974	12.34

3.2.2 Proportion of Matches Within the Sample

In total, there were 1835 instances where a day had at least one CM-DM match, this represents 68.80% of the 2667 reported DM. Table 3.3 shows the frequencies for all reported DM that had at least one CM match in the same day.

Table 3.3: Frequencies of DM that had at least one CM match.

mood	count	percentage
neutral	93	5.07
tense	92	5.01
excited	93	5.07
happy	455	24.80
relaxed	569	31.01
calm	219	11.93
bored	146	7.96
upset	59	3.22
stressed	109	5.94

3.2.3 Data Transformation

Since the data was longitudinal and participation was voluntary, each participant had a varying number of data points. To maintain independence of observations, the data was modified to summarise the instances per participant. This involved either adopting the count (number of matching or non-matching current and evening survey pairs), the median (time difference between current and evening surveys, intensity of the current mood reports) or calculating a percentage (number of matching current-evening mood pairs per day) of all instances concerning a participant.

3.3 Results

3.3.1 Comparison of proportion of matches/non-matches to random

A binomial test was used to compare the proportion of matches and non-matches between CM and DM responses against the number of such matches that would occur in a random sample ($1/9 = 11\%$). The proportion of matches was statistically greater than 11% ($p < .001$) with 2529 (32.04%) of the CM and DM survey pairs reporting the same mood.

3.3.2 Effects of Individual and Intrinsic Characteristics

The Percentage of Matching CM-DM pairs (PM) was not normally distributed, therefore non-parametric tests were used. The effect of demographic variables and the percentage of matches were analysed using the Wilcoxon-Mann-Whitney test and Spearman's correlation. No statistically significant difference was found for gender (Z = -1.729, p = .084) nor age (r_s = .175, p = .167) in association with the PM per day from the total CM-DM pairs.

Moreover, the PM was evaluated against a variety of traits using Spearman's correlation. The PM was found not to be correlated to any of the Big Five personality traits: openness (r_s = -.420, p = .744), conscientiousness (r_s = .060, p = .636), extraversion (r_s = .085, p = .503), agreeableness (r_s = .059, p = .641), and neuroticism (r_s = -.189, p = .153). The PM was also not correlated to the Smartphone Addiction Scale score [110]. This was true for the participants' score for both the briefing (r_s = -.100, p = .430) and debriefing (r_s = -.024, p = .851) sessions. The PM was also not correlated to the impulsivity score given by the MCQ. This was also true for both the briefing (r_s = -.039, p = .760) and debriefing (r_s = -.001, p = .991) results. No significant differences were found for any of the other investigated individual characteristics: bilingualism (Z

= -.840, p = .401), participant's first language ($\chi^2(12)$ = 17.754, p = .123), employment status ($\chi^2(6)$ = 4.639, p = .591), education level ($\chi^2(6)$ = 8.839, p = .183), handedness ($\chi^2(1)$ = .013, p = .910), handedness during smartphone use ($\chi^2(2)$ = 4.346, p = .114) and estimated smartphone usage in relation to population average ($\chi^2(2)$ = 5.476, p = .065).

3.3.3 Effects of Mood Report Characteristics

The intensity of reported CMs and the time interval between CM and DM were investigated. Considering days with matches only, a binomial test was performed comparing the proportion of cases where the matching CM had the highest recorded intensity for that day with the proportion expected by chance (52%). With 71% of matching CM reports, the intensity of the reported CM was revealed to have a significant effect on the CM-DM match ($p < .001$). Similarly, the positive valence of reported CMs was analysed. The binomial test revealed that the proportion of matching CMs which had the highest recorded positive valence for that day (66%) was significantly higher than the proportion expected by chance (46%). Additionally, Chi Square tests were performed, which confirmed that DM reports had a significantly higher number of positive ($\chi(1) = 67.218, p < .001$) and a significantly lower number of negative ($\chi(1) = 8.229, p = .004$) reported moods in comparison to CM reports.

As the time intervals were not normally distributed, a Wilcoxon-signed ranks test was performed. The median time between evening and current mood surveys was significantly shorter for matches than non-matches (Z = -3.103, p = .002), with matches having a median time difference of 19045s (5.29hrs) and non-matches having a median time difference of 21465s (5.96hrs).

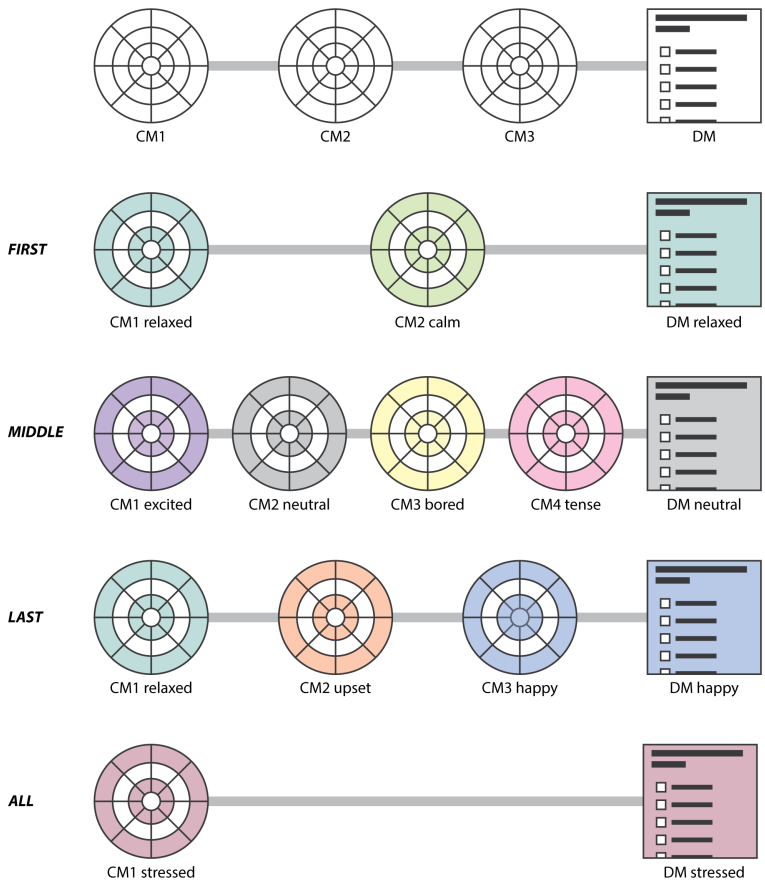


Figure 3.3: Examples of days that have at least one CM-DM match and what they would be classified as. The same colour represents the same reported mood.

3.3.4 Effect of Time on CM-DM Report Matches

To investigate how time might have affected the match of current and daily mood surveys, we examined the order in which matches and non-matches took place within a day. For each participant, the number of days was counted in which matches in mood response occurred, using categorisation as follows: ALL, where all reported current moods of the day match the reported evening mood, FIRST, LAST and MIDDLE where the reported CM(s) of the day that matched the reported DM respectively were the first, last and neither first nor last, however, requiring that there was at least one match throughout the day. Examples of how a day could be allocated in any of the categories is shown in Figure 3.3. Since days that had both matches for the first and last reported CM would fall into both of these categories, they were split evenly between them (see Figure 3.4). The resultant categorisation was therefore mutually exclusive. It should also be noted, that, since a day was defined as starting at 00:00 and ending at 23:59, some matches (including the LAST match) could have occurred after the evening survey was completed.

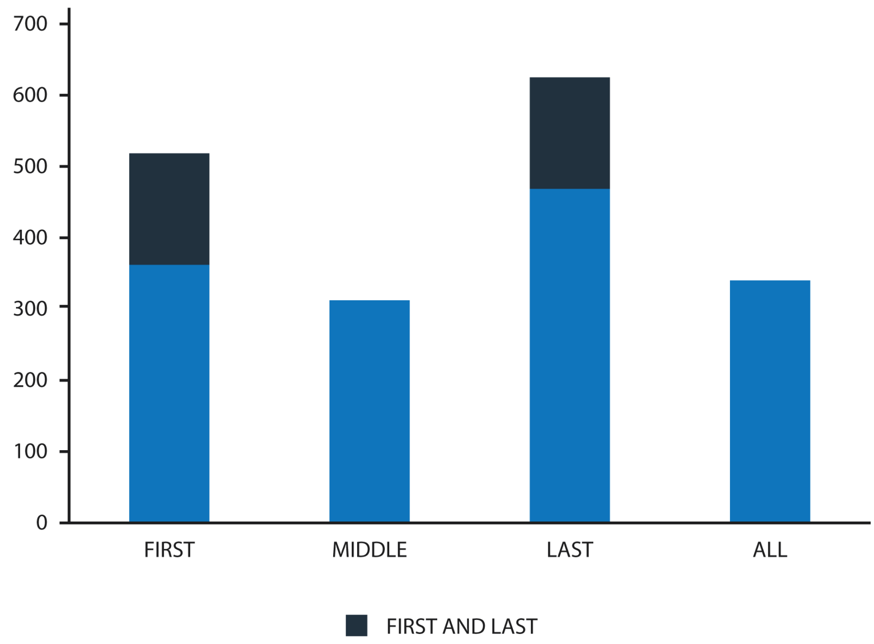


Figure 3.4: Number of days with matches for each of the categories.

Due to the non-normality of all variable distributions, Wilcoxon's signed rank test was used to compare all categories to each other. Matches in the LAST category were found to be significantly more frequent ($p < .01$) than occurrence in other categories ($M = 8.24$, $SD = 5.44$), followed by matches in the FIRST category ($M = 6.57$, $SD = 4.49$) which were statistically smaller ($p = .006$) than those in the LAST category and greater ($p < .01$) than ALL ($M = 5.31$, $SD = 4.40$) and MIDDLE ($M = 1.89$, $SD = 3.12$) categories, which in turn were not significantly different from each other ($p = .888$). These results are also shown in Table 3.4.

Table 3.4: Z values for each category pair.

	FIRST	ALL	MIDDLE	LAST
FIRST	-	-2.664**	-2.875**	-2.730**
ALL		-	-.140	-4.103***
MIDDLE			-	-4.748***
LAST				-

*p<.05, p**<.01, p***<.001

3.4 Discussion

This study has shown that there is evidence to suggest that CM and DM reports are interchangeable as a methodology to sample participant mood. Indeed 68.8% of the recorded DM matched a CM that was reported in the same day. None of the investigated intrinsic human characteristics (gender, age, personality, impulsivity, smartphone addiction-proneness, etc.) had an effect on matches of current and daily moods, suggesting that a specific participant sample would not justify the choice of one over the other reporting method. This is a positive finding that supports the use of smartphones for experience sampling.

Further results show that time intervals between CM and the DM survey had a significant effect on CM-DM matches. This could imply that the daily mood does not reflect as much the entirety of the day as the formulation of the survey question intended. As predicted by memory biases, the last reported CM reports were more likely to match the DM report due to them being closer in time. The mood reported in the last daily CM survey might still match the participant's mood state at the time of the DM report, further biasing the participant towards picking the same mood for the DM survey. The first reported CM report came in second in terms of similarity. These findings are consistent with reports of the Serial Position Effect [141]. Furthermore, the intensity and valence of CM moods were revealed to have a significant effect on CM-DM matches too, with the matching CM most often being the mood with the highest reported intensity and the most positive mood of that day. This result is consistent with the Peak-end rule [73] and the Fading Affect Bias [202]. These results indicate that when CM reports are chosen over DM reports, including an intensity measure may be of interest to identify a day's most prevailing mood(s).

This implies that CM reports might be more accurate to sample current mood than DM reports are for collecting daily mood since memory biases come into play that hinder the formation of an accurate daily summary.

Looking at overall survey completion rates (see Section 2.3.2), DM surveys were also at a disadvantage considering the number of dismissed notifications. Indeed, prompts for CM surveys were less frequently swiped away (7.04%) than for DM surveys (12.59%), while the percentage of survey completions via the app interface is comparable for both methods (5.69% for CM vs 6.44% for DM). However, participants might have felt less of a need to dismiss notifications for CM as they expired more quickly in the experiment, due to the requirement for repeated sampling (see Section 2.2.2). CM were more invasive as participants were prompted up to three times a day or even more if they chose to dismiss the notifications instead of completing the task. DM surveys however only happened once a day at a set time, which participants could easily get used to. This is likely to have contributed to an overall higher completion rate for DM (79.35%) than CM (61.06%) reports.

3.5 Conclusion

In conclusion, whether current mood surveys or daily mood surveys should be used to collect affective data on participants highly depends on the requirements of the study, and whether related *in-situation* context or device usage is important. One also needs to consider what exactly needs to be collected: momentary mood fluctuations, which can vary throughout the day, or prevailing mood of the day, which relies on the capabilities of participants to summarize 24 hours of mood variations into a single response.

However our results indicate that both approaches can be used with confidence, albeit noting specific implications for each.

We note that while the investigated participants' intrinsic characteristics did not influence the accuracy of one survey type over the other, effects for time and intensity that could be attributed to memory biases did come into play. Current mood surveys are more likely to be accurate as the participant is directly asked for the mood state that they are in at that instant, while a daily mood survey requires the participant to provide a summary of the mood states they have felt during the day and this cognitive task is vulnerable to memory biases. If participant compliance is of high importance however, daily surveys should be considered as participants will be more likely to dismiss notifications if they are frequent or if these come at inopportune moments in contrast to a set time.

This chapter constitutes the following contribution (see Section 1.5) to this thesis:

C2 Comparison of two sampling frequencies of mood for ESM data collection: discussion of advantages and disadvantages.

The findings of this chapter informed the use of DM reports in Chapter 5 and the consideration of both CM and DM reports in Chapter 6.

Chapter 4

User Interactions and Smartphone Addiction

Parts of this chapter have been published in the peer-reviewed journal Computers in Human Behavior:

Beryl Noë, Liam D Turner, David E Linden, Stuart M Allen, Bjorn Winkens, and Roger M Whitaker. Identifying Indicators of Smartphone Addiction Through User-App Interaction. *Computers in Human Behavior*, 99:56-65, 2019.

In this chapter, we seek to identify what types of smartphone usage activities are associated with SA. In contrast to other studies that have used self-reporting or the timing of activity sessions to quantify smartphone usage, we base our measure on the amount of physical interactions with the interface (e.g., taps, scrolling and typing). This method is novel because it differentiates between active and passive usage and directly encapsulates potential problematic physical smartphone behaviour as a signal. Therefore we believe it has the potential to identify latent characteristics of usage that may not be evident to the user from self-reflection. Accordingly we investigate this in detail, with a view to determining how the SA assessment associates with variables capturing user interactions with the device.

4.1 Introduction

As highlighted in Chapter 1, smartphone usage has become ubiquitous across much of the global population and increasingly high daily usage levels have been reported [53]. Evidence of dependency and attachment to smartphone technology [88], combined with the potential disruptiveness of incoming notifications [191, 192], and "checking habit" formation [146] have now been acknowledged as potentially harmful and recognised as SA [149]. Problematic smartphone use has been linked to teenage depression and anxiety [83, 121], and more widely, various relationships have been found concerning stress, depression, sleeping problems, anxiety, subjective well-being, and loneliness [54, 61, 120, 121].

Despite this research progress, detecting indicators of problematic smartphone behaviour is a challenge for two main reasons. Firstly, the range of utility that smartphone apps provide means that usage levels are generally high and that high usage is socially acceptable [43]. Therefore behaviour correlating with SA can easily be hidden. Secondly, apps increasingly allow the smartphone to be passively used for large periods of time as a substitute for other devices (e.g., GPS navigation, TV, music player) meaning that as smartphone usage gets more diverse, high level metrics, such as time on the smartphone, may not represent the strongest indicator of problematic behaviour. These issues contribute to the invisibility of SA [161] and the challenge of encouraging behaviour change to avoid it.

By examining *all* interactions that a user performs through physically touching the screen (e.g., typing, scrolling, tapping), we are able to consider detailed user-app interactions as an indicator for SA. This allows us to gain new insight into the potential sources of problematic behaviour and pathways to addiction. In particular, our approach is based on measures of *active* usage than *passive* usage, which is determined by the extent of user engagement with the interface while the smartphone is operational. It also avoids the need for self-reporting and goes beyond the convention of monitoring screen or app time. The bespoke smartphone application *Tymer* introduced in Chapter 2 allowed us to collect data for this analysis. We note that unlike previous work, the approach of assessing all the user's interface interactions allows us to examine a wide range of apps within a single study, and make relative comparisons between different apps and classes of apps.

4.2 Related Literature and Hypotheses

Assessments for SA have resulted in various self-diagnostics as outlined in Section 2.2.1, with the Smartphone Addiction Scale [110] in particular combining assessment of substance use disorders, Internet Addiction, and the smartphone's own features. Current research related to SA frequently considers a particular application (e.g., Facebook [165], WhatsApp [139]) or a class of apps (e.g., social networking [168]). In this context it is important to note that SA can, like Internet Addiction [80], be argued to be both source and pathway to the causes of addiction.

4.2.1 Motivating Issues

Historically, high usage, measured by time, has been shown to be a key element of SA (e.g., [17, 53, 119, 121, 161, 163]). Differences in time spent on smartphones is often attributed to habit [146, 189] and usage frequency [189]. However, as smartphone capabilities continue to increase and support a wider variety of apps, it becomes important to determine the extent to which SA is related to particular types of use. Active usage, where the user is engaged through UI interactions, as compared to passive use (e.g., video streaming), remains an important distinction. To the best of our knowledge, this distinction has not been studied in the literature, due to the additional complexity required in assessing a user's interactions at a granular level. We focus on this and determine the interaction events occurring at the user interface. Based on previous observations regarding time, it is appropriate to hypothesise that *high-scorers in*

SA have more UI interactions than low-scorers (H1); this can be considered across all applications.

It is challenging to assert with confidence how SA may manifest itself in terms of specific types of UI interactions, relative to the broader user population. Social media has been reported as one of the top reasons for smartphone use. In particular, social networking applications were found to be the second most downloaded type of application after games [123] and social networking accounted for the most application launches, representing 18% of the total number of launches in front of browser and search launches at 14% in recent assessments [35]. According to Statista [181], daily time spent on social networking is on the rise, reaching an estimated 135 mins in 2017, representing an eighth of the time spent awake by an average adult. Social media has also been linked to SA in teenagers [95] and adults [65]. Large networks and high participation intensity in networks seem to contribute to the use of social media apps and SA [168]. Facebook [25, 161, 165], Twitter [161], and Instagram [161] in particular have been identified as social media platforms whose use seems associated with SA. Recent work [158], examining the user's relationship with the Snapchat social media app has posited that a user's functional and entertainment needs correlate with Internet Addiction. Interestingly, social media addiction has also had the highest correlation to Internet Addiction [138] in comparison to a number of addictions to other online activities: gaming, shopping, social networks, and pornography. *We therefore hypothesise that high-scorers in SA have more UI interactions on social media applications (H2)*, with particular reference to Facebook, Instagram and Snapchat [25, 158, 161, 165]. This translates as a greater number of UI interactions registered across the Social apps category.

Closely related to social media, the communication function of smartphones has been retained as one of the central activities for users [31, 35], despite the extended role of the smartphone as a pocket computer. Messaging [119, 121, 214, 117] and phone calls [161, 214] have previously been associated with SA. Texting has also been found to be positively related to the mobile phone interfering with life [52]. In comparison to Facebook however, little evidence for links to SA have been found for Facebook Messenger and WhatsApp, two of the most popular communication apps worldwide. Overall, the messaging literature points to supporting the proposition that *high-scorers in SA will have more UI interactions supporting communication activity (H3)*, detectable in our context from a larger number of user-generated events on the Communication apps category.

4.2.2 Summary of Hypotheses

The hypotheses involve testing the extent to which UI interactions, at the most granular level possible, are indicative of SA. In summary:

> *H1:* SA score is positively associated with the number of UI interactions with the device.
>
> *H2:* SA score is positively associated with the number of UI interactions on apps of the Social app category, with particular reference to Facebook, Instagram, and Snapchat.
>
> *H3:* SA score is positively associated with the number of UI interactions on apps of the Communication app category, with particular reference to WhatsApp and Facebook Messenger.

To the best of our knowledge, these hypotheses have not been previously tested and therefore the significance of UI interactions as an indicator of SA has not been established. We address the hypotheses in the context of an exploratory study, where wider observations are also presented. We investigate the hypotheses from three perspectives: the different types of UI interactions, as detected through machine-readable actions; the UI interactions with different apps and the UI interactions with different categories of apps. This also allows us to gain new potential insight into the sources of problematic behaviour and pathways to addiction. The specific interactions generated relate to tapping (short and long), writing, scrolling and text selection.

4.3 Methods

Data analysed in this chapter was collected through the *Tymer* application and through surveys held during the briefing and debriefing sessions. How this data was collected is described in more detail in Section 2.2. The data from 64 participants was used in this study.

We use the following data for the assessment of SA:

- Demographics data: gender, age
- Survey data (briefing and debriefing):
  - SA score
- Smartphone usage data:
  - Type of data: Human-smartphone interaction events (taps, long taps, scroll, writing, selection)
  - Sources of data: specific apps (Snapchat, Facebook Messenger, Facebook, WhatsApp, WeChat, YouTube, Instagram, Google Play Store, Google Calendar), specific app categories (Auto And Vehicles, Business, Communication, Entertainment, Finance, Game, Health And Fitness, Lifestyle, Maps And Navigation, Music And Audio, News And Magazines, Personalization, Photography, Productivity, Shopping, Social, Sports, Tools, Travel And Local, Video Players)

A paired t-test was carried out to check whether the participant population's results for the Smartphone Addiction Scale tests had significantly changed between briefing

($M = 89.39, SD = 23.41$) and debriefing sessions ($M = 86.28, SD = 19.22$). This was not the case ($p = .077$) and the test values were highly correlated amongst themselves ($r = .807, p < .001$). For this reason, we used the mean of both tests for the analyses, which focus on user interactions with their device captured though the *Tymer* app. Each interaction is referred to as an *event*, recorded alongside a time stamp and the source of the event (i.e., the application with which the user interacts). As previously highlighted (see Section 2.3.3), only UI interaction events (i.e., tap, long tap, writing, scroll, and text selection) are considered to specifically capture *active* and avoid including *passive* usage in our measures.

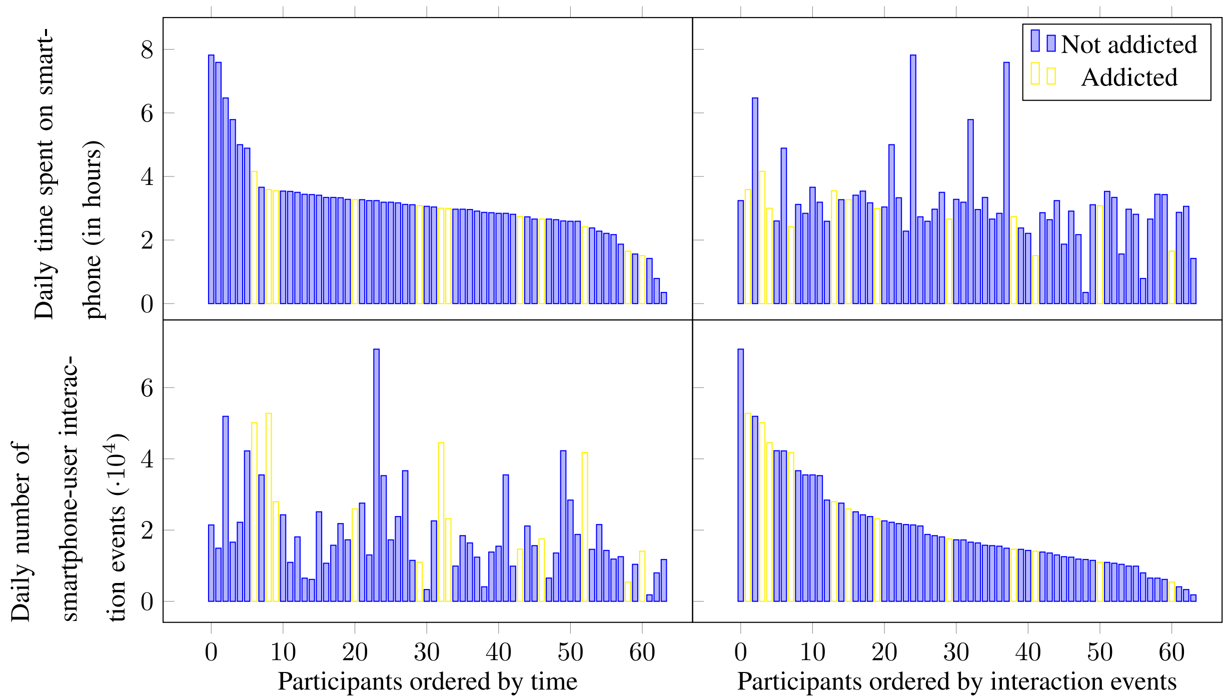


Figure 4.1: Daily usage of non-addicted and addicted users (N = 64).

In Figure 4.1 we present descriptive statistics concerning smartphone usage, for users classified by their addiction status, as determined by the SAS-SV [109]. In the left panel, users are ordered by descending daily time spent on the smartphone, and notably, addiction is widely spread across the distribution. The same data is presented in the right panel, but with the users ordered by decreasing number of daily UI in-

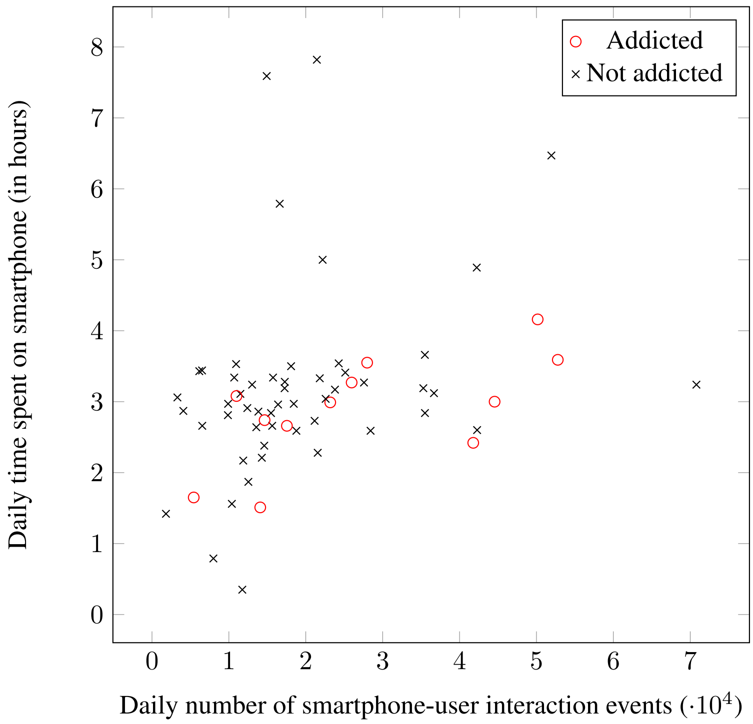


Figure 4.2: Daily usage of non-addicted and addicted users by time spent on phone (N = 64).

teractions. Here there appears to be increased clustering of SA for users at the head of the distribution. The relationship between daily time on the smartphone and UI interactions is further expressed in Figure 4.2. Note that for the smartphone addicted sub-group, there is much greater variance in UI interactions, as compared to daily time on the smartphone.

4.3.1 Analysis Design

From comparing the number of events between participants, we analyse differences in participants' usage behaviour. The sum of events was chosen as the principle variable rather than a total session time length since it requires no interpretation of the data and represents the intensity of smartphone-user engagement. The data was normalised to obtain the average daily number of events, to account for any deviations in participation, such as from choosing to opt out or a delayed start. It should be noted that different apps generate different types and volumes of events. However this is not an issue in this study since we are principally concerned with analysing inter-personal differences relating to the same app or category of apps.

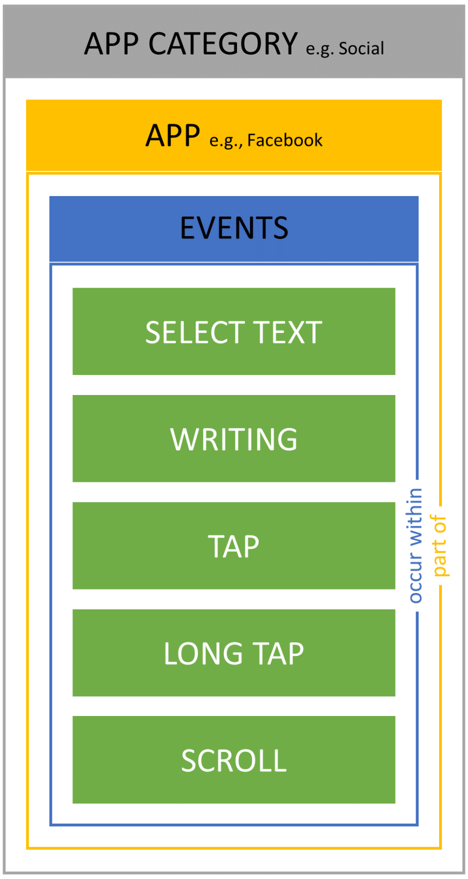


Figure 4.3: The relationship between events, apps and categories of smartphone applications.

Figure 4.3 shows how user behaviour can be captured through total events of different types, that occur within different apps belonging to different categories of apps. These provide different levels of aggregation for a user's interaction and we consider their correlation with SA. A more detailed overview of this is given in Section 2.3.3 and particularly Figure 2.4.

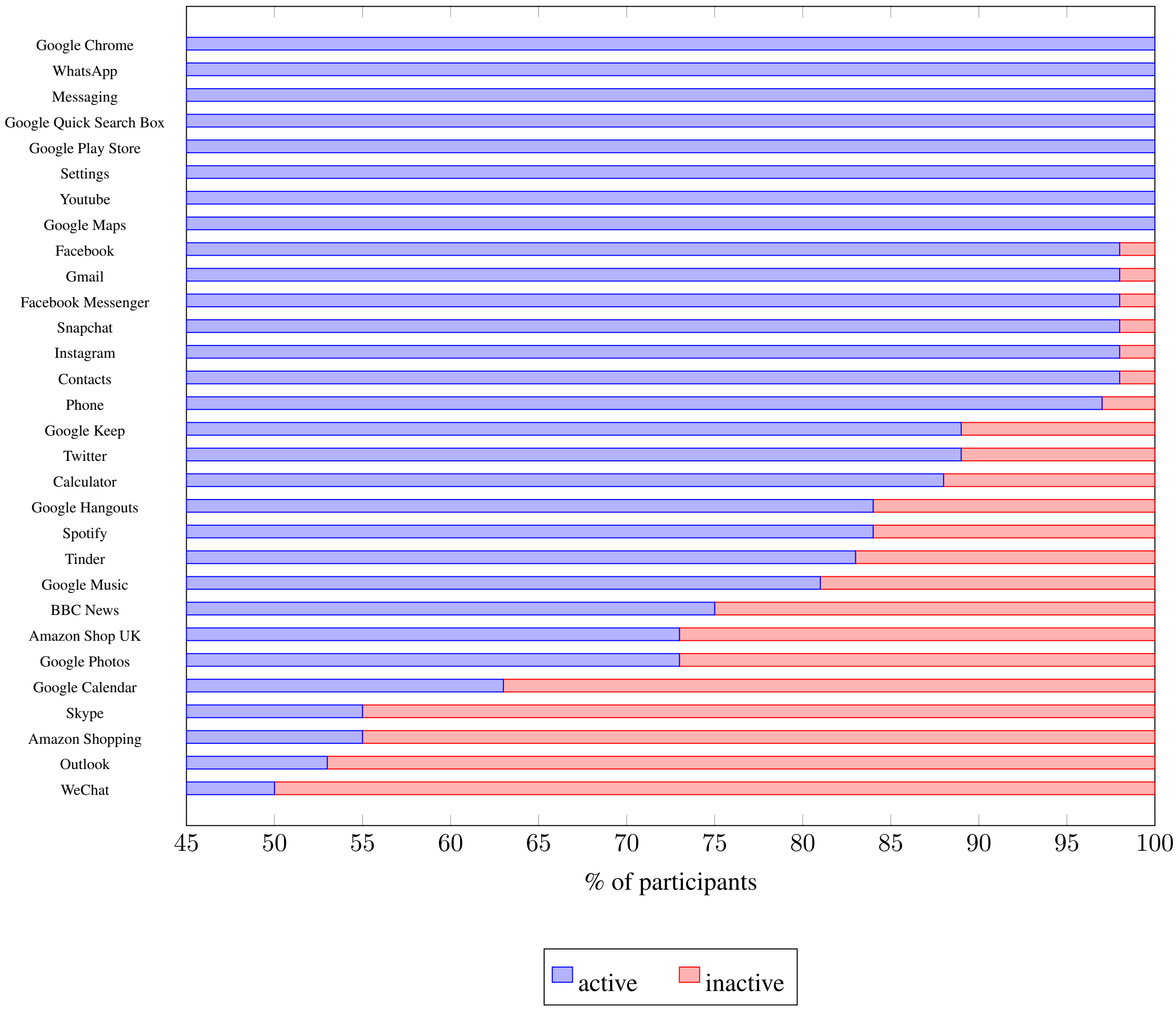


Figure 4.4: Percentage of participants having at least one recorded UI interaction event, i.e., being active on popular apps (N = 64).

Events within app categories capture broad user behaviour, and can be modelled by the approximate taxonomy provided by the Google Play Store. No changes were made to these categories, with the exception of game app subcategories that were aggregated into a single Game category. Uncategorised apps were not included in the analyses pertaining to app categories. To allow cross comparison, app categories used by less than half of the participants were excluded, resulting in a list of 21 app categories (see Table 4.1). Considering events within apps provides insight into behaviour aligned with a particular bundle of functionality. Again, only sources from popular apps were included; apps that were absent from at least half of the participant's data and smartphone brand specific apps were excluded, resulting in the consideration of 29 apps (see Figure 4.4). The total number of events across all apps was computed for each event type in isolation. These are potentially indicative of variations in overall usage between users. The types of events considered relate to a tap, long tap, writing, scroll, and text selection.

Gender and age are known characteristics likely to influence smartphone usage [53, 161]. To account for these confounding factors in each analysis, partial Spearman correlations with SA were first carried out separately for each gender, using age as a covariate. If the correlation coefficient was of the same sign, the analysis was repeated combining both male and female participants, and using both age and gender as covariates.

To correct for possible occurrence of type I errors, a False Discovery Rate (FDR) method was applied using the Benjamini-Hochberg procedure [21].

4.4 Results

Participants received a mean score of 87.84 ($SD = 20.28$) on the SAS. Neither gender was more or less likely to be addicted to smartphones than the other ($t(62) = .257, p = .614$). The mean SA score obtained by male participants was 89.01 ($SD = 21.10$), while it was 86.51 ($SD = 19.57$) for female participants. Moreover, age was not significantly correlated to SA ($r = .219, p = .082$).

When the daily amount of time spent on smartphones was evaluated in relation to SA, no significant association was found for males ($r = -.073, p = .685$), females ($r = .351, p = .062$), and across gender ($r = .150, p = .244$). This formalises the observations made on the descriptive statistics in Section 4.3 (Figure 4.1) where SA is seen across participants with wide ranging daily time on the smartphone. This may indicate that passive usage, characterised by high time periods using the smartphone

Table 4.1: Application categories use correlation with Smartphone Addiction for male (a), female (b), and all users (c).

App Categories	(a) M r	(a) M p	(b) F r	(b) F p	(c) M+F r	(c) M+F p
Auto And Vehicles	.230	.198	.013	.948	.105	.416
Business	.066	.713	.228	.234	.159	.216
Communication	.100	.581	.011	.953	.048	.711
Entertainment	.068	.708	.075	.700	.068	.601
Finance	.068	.708	.187	.332	.200	.118
Game	.062	.730	.093	.631	.109	.401
Health And Fitness	.131	.468	-.066	.732		
Lifestyle	.230	.199	.680	.000*†	.446	.000*†
Maps And Navigation	.284	.109	.337	.074	.322	.011*
Music And Audio	.007	.971	.169	.381	.062	.630
News And Magazines	.205	.252	.195	.310	.198	.122
Personalization	.111	.537	.270	.157	.151	.241
Photography	.165	.360	.011	.957	.117	.364
Productivity	.148	.412	.036	.851	.120	.353
Shopping	.064	.724	.142	.464	.085	.510
Social	.364	.037*	.445	.016*	.421	.001*†
Sports	.234	.191	.014	.944	.123	.341
Tools	.495	.003*	-.117	.546		
Travel And Local	.177	.323	.040	.835	.143	.268
Video Players	.098	.586	.085	.661	.090	.488

* $p < .05$

† FDR < .05

with low levels of UI interaction, could be a common use case in smartphone usage. This provides evidence that alone, time on the smartphone does not necessarily provide a strong indicator of problematic smartphone behaviour, and further motivates the analysis of UI interaction as an indicator of SA, as considered in the following analyses.

4.4.1 UI Interactions in App Categories and Smartphone Addiction

From considering total events by app category, analysis was undertaken based on gender, assessing each gender in isolation and also together (Table 4.1). These analyses allow investigation of Hypotheses *H2* and *H3*.

For female participants, SA was linked to Lifestyle ($r = .680, p < .001$) apps. When both genders were considered together, correlations were found with Lifestyle ($r = .446, p = .001$) and Social ($r = .421, p = .001$) app categories. This is consistent with previous findings by Montag and colleagues [138] concerning social media addiction. Evaluating different types of internet addictions with generalised IA, they find social media addiction overlaps most extensively with IA.

These results support Hypothesis *H2*, however a significant correlation with social apps only occurs when combined analysis is performed on gender; this is likely due to limitation in sample size for the gender specific analyses. Interestingly the results do not support *H3*, with the Communication app category not being significantly correlated to SA. It may well be that the multifaceted functionality of social media is permitting new channels through which traditional text based-communication can be undertaken.

4.4.2 UI Interactions Within Apps and Smartphone Addiction

While considering the total UI interaction events generated in each app in isolation, analysis was undertaken based on gender, assessing each gender separately, followed

Table 4.2: Application use correlation with Smartphone Addiction for male (a), female (b), and all users (c) for a subset of analysed apps.

Apps	(a) M r	(a) M p	(b) F r	(b) F p	(c) M+F r	(c) M+F p
Communication						
Contacts	.459	.007*	-.182	.344		
Facebook Messenger	.204	.254	-.129	.505		
Gmail	-.037	.840	-.033	.867	-.037	.777
Google Chrome	.177	.325	-.135	.486		
Google Hangouts	.084	.642	.126	.516	.058	.655
Skype	.045	.805	-.318	.092		
WeChat	.094	.602	.281	.139	.183	.155
WhatsApp	.159	.376	.331	.079	.210	.102
Social						
Facebook	.324	.066	.176	.361	.309	.014*
Instagram	.358	.041*	-.017	.931		
Snapchat	.326	.064	.548	.002*	.386	.002*†
Lifestyle						
Tinder	.086	.634	.203	.292	.121	.348

* $p < .05$

† FDR < .05

by analyses across genders. Table 4.2 shows the correlation scores for the apps relevant to Hypotheses *H2* and *H3* and from the app categories that were found to be significantly correlated to SA. Consistent with the previous analysis of app categories, none of the communication apps were significantly correlated to SA. However, Snapchat, an app from the Social category, was found to be significantly correlated to SA ($r = .386, p = .002$). This is an interesting finding, consistent with Snapchat providing more than only functional user experience relating to pleasure and entertainment. However, in contrast to previous research [158], addiction to Snapchat appears more significant than for other social media applications.

These results partially support Hypothesis *H2*, but the non-significant findings for the social media applications Facebook and Instagram were not foreseen. While Snapchat is not classified in the app store as a communication application, aspects of its functionality lend themselves to a process of targeted information exchange, lending some partial but weak support for Hypothesis *H3*.

It is also notable that, while positive correlations were found for the Lifestyle category, Tinder, the only app analysed in isolation from this category had no significant correlation to SA.

4.4.3 UI Event Types and Smartphone Addiction

To investigate Hypothesis *H1*, UI interaction events were considered by each different type (tap, long tap, writing, scroll, text selection and all combined, see Table 4.3). When both genders were combined, overall usage ($r = .280, p = .028$) and scrolling ($r = .284, p = .025$) events were found to be positively correlated to SA. However, these results were not significant for FDR < .05. This partially supports Hypothesis *H1*.

We note that even though tap, long tap, writing, and text selection events were not significantly associated with SA when all app data was considered, they were in the context of Snapchat. This is likely due to the overall strong correlation of Snapchat usage, regardless of the interaction type. This is especially true for female users.

Interestingly, long tap events (used to bring up context menus) in the Contacts built-in application were significantly correlated to SA for male users only. The strong correlations found for other event types (albeit not significant for FDR < .05) suggest that

Table 4.3: Correlation between app usage per event type and Smartphone Addiction for male (a), female (b), and all users (c) for a subset of analysed apps for which at least one p < .05 result was found.

		(a)		(b)		(c)	
Event type	App	M		F		M+F	
		r	p	r	p	r	p
All	all	.303	.087	.253	.186	.280	.028*
Tap	all	.170	.344	.241	.207	.226	.078
	Contacts	.427	.013*	-.187	.331		
	Facebook	.363	.038*	.103	.596	.307	.015*
	Google Quick Search Box	.344	.050*	.242	.207	.315	.013*
	Instagram	.345	.049*	-.004	.984		
	Snapchat	.322	.068	.645	.000*†	.459	.000*†
Long tap	all	.142	.431	.241	.207	.210	.101
	Contacts	.485	.004*†	-.069	.720		
	Facebook	.321	.068	.105	.587	.260	.042*
	Google Quick Search Box	.284	.109	.307	.106	.283	.026*
	Snapchat	.240	.178	.498	.006*	.368	.003*†
Writing	all	-.053	.770	.327	.083		
	Contacts	.496	.003*	-.226	.239		
	Facebook	.273	.124	.198	.304	.259	.042*
	Google Play Store	.320	.069	.240	.210	.277	.030*
	Google Quick Search Box	.412	.017*	-.067	.728		
	Snapchat	.281	.113	.620	.000*†	.432	.000*†
	Spotify	.106	.557	.481	.008*	.261	.040*
Scroll	all	.406	.019*	.159	.410	.284	.025*
	Facebook	.285	.024*	.159	.409	.295	.020*
	Google Quick Search Box	.265	.037*	-.066	.734		
	Settings	.359	.004*	.246	.198	.326	.010*
	Snapchat	.346	.006*	.459	.012*	.347	.006*
	WhatsApp	.260	.042*	.322	.088	.276	.030*
Text selection	all	.123	.497	.295	.120	.142	.270
	Contacts	.419	.015*	-.343	.068		
	Facebook	.373	.032*	.119	.537	.287	.024*
	Google Play Store	.404	.020*	.168	.385	.316	.012*
	Google Quick Search Box	.456	.008*	-.074	.705		
	Snapchat	.323	.067	.536	.003*	.411	.001*†
	Spotify	.153	.396	.418	.024*	.262	.039*

* p < .05

† FDR < .05

this result might be due to the overall correlation of Contacts use and SA. No significant correlations were however found for scroll events, which is of particular interest as they are the most used type of UI interaction overall (see Figure 2.5 in Section 2.5). We also note that no significant correlation could be established for female users.

These results further provide some support for Hypotheses *H1* and *H2*, with weak support for *H3* when male usage of the Contacts app and the communication function of Snapchat is considered. Again it is notable that as compared to Facebook and Instagram, interaction with Snapchat has a more statistically significant correlation.

4.5 Discussion

The results provide some evidence for Hypothesis *H1*, noting that overall usage and scrolling events appear positively correlated to SA, when taken on aggregate (Section 4.4.3), although they do not withstand FDR correction. When considering events by their source application (Section 4.4.2), Snapchat was repeatedly found to be an origin from which particular events significantly positively correlate with SA. This also supports social media being a source of high activity for smartphone addicts (Hypothesis *H2*). Indeed, we find that across the categories of apps (Section 4.4.1), level of engagement (i.e., total user-generated events) in the Social category significantly correlates with SA, in support of Hypothesis *H2*. It is notable that the Lifestyle category is also significantly correlated with SA (Section 4.4.1). However, the findings in support of *H2* are limited to correlation with activity in Snapchat, rather than a broader range of social media applications. This appears to provide a differential between Snapchat and other forms of social media, which was not anticipated based on the previous literature. Little support for Hypothesis *H3* was found, which may be due to social media apps implicitly providing communication functionalities. However, usage of popular messaging apps, such as WhatsApp, was not found to be significantly correlated with SA.

Correlation between Lifestyle apps and SA was not hypothesised to be significant. Tinder is the only Lifestyle app that was analysed in isolation in our app analyses, however no significant relationship was found between its use and SA, for both genders. Given the diversity of potential Lifestyle apps, it is therefore difficult to establish any common characteristics of the Lifestyle apps used that contribute to correlation with SA, especially in the case of female users ($r = .680$). Since Lifestyle apps are diverse and indeed linked to a certain lifestyle that might widely differ per individual, it is perhaps the higher interaction with personalised, non-mainstream apps that is the basis of SA in this context. The gender difference might be explained by the greater brand commitment women showcase [188], the difference between how male and female users personalise their phones [190], and that a large portion of top apps seem to target topics which in general, women display more interest in than men [51, 71].

Focusing on the findings for social media however, the results suggest that assessment of the user's device interaction is a useful proxy for Smartphone Addiction assessment. Importantly, the results show utility in observing UI interactions at a detailed level, and provide a means to filter false positive results that occur due to passive use of the smartphone. Our findings are consistent with the general literature that correlates social media usage with SA [52, 65, 95, 165, 168] and the Fear of Missing Out (FoMO) [8, 157], which has been previously aligned with problematic usage [63]. However, the prominence of Snapchat, relative to other social media apps, is a particularly interesting aspect in our results. This is significant because Snapchat is heavily used in the wider population, and is attractive to teenagers [179]. While concerns have been voiced in the wider press on the addictive nature of Snapchat [10, 98, 185, 211], to the best of our knowledge, limited academic research has been conducted to date [158].

4.5.1 Pathways to Addiction

Smartphone usage provides pathways to addiction on several distinct levels. Firstly, the ease of access combined with the widespread and socially accepted use of smartphones, makes smartphone use ubiquitous. Secondly, the increasing number of functionalities smartphone (apps) offer, make users more reliant on the technology and incentivise smartphone usage over analog options or other digital devices. Thirdly, apps are designed to make users prolong their usage (e.g., through "infinite scrolling" which lacks any stopping cues) or come back to them (e.g., notifications or daily rewards urging the user to open the app). In our fine-grained analysis of UI interaction events within applications, we have attempted to look more closely at this third phenomenon. Observing UI interaction directly engages the potential problematic behaviour as a signal. This also reduces the opportunity for false positive problematic use classification to arise for users who have high levels of passive usage, such as occurs through streaming media or using the smartphone as a GPS device.

Beyond interaction with the device, the bundled nature of apps gives a multitude of ways through which app design and user experience may further contribute to problematic behaviour. FoMO is applicable across all social media apps and therefore characteristics beyond this are relevant. In particular, it is conceivable that the particular design of the Snapchat app contributes to the significant correlations that are repeatedly evident in our analyses, as compared to other social media apps (e.g., Facebook, Instagram).

We note that Snapchat is distinct from other social media in providing multimedia messaging whose main feature is the ephemeral nature of the text, picture or video messages. Snapchat has a combination of design features that promote high frequency usage. For example, "friend emojis" appear next to a user's friends' names only if they "snap" each other regularly and feedback is provided on when content has been consumed by the recipient. The app's functionality, in terms of filters used to visually edit content, also regularly changes. The self-deleting nature of content and the way in which messages are sent creates a perception of control and privacy [197]. Incentives are also provided for users to increase their snapping frequency (i.e., send new content), by effectively making friends compete against each other for top position and incentivising them not to break their "Snapstreak" (which is only maintained if both interaction partners have sent each other a Snap within the last 24 hours). This latter form of gamification promotes usage, but it may also promote addiction [86]. Additionally, in contrast to some other social media platforms, Snapchat is only available for smartphones (as opposed to a general web application), channelling all usage through the handset.

Interestingly, the Snapchat app also connects with entertainment aspects of social communication, with "chatting through pictures" providing a strong emotional context as compared to text [201]. The combined need for the app to support fun and functionality has been previously linked to Snapchat addiction [158], when Snapchat usage is considered in isolation. Based on our findings, we hypothesise that the design features of Snapchat, relative to other social media apps, are providing a strengthened environment for SA to take hold.

4.5.2 Limitations

Although equal or greater in sample size than other observational and task based studies (e.g., [11, 129, 150, 205]), it is possible that, given the power of the present study, we did not detect all true associations, and thus replications with larger samples may reveal additional findings. We also note that due to the properties of different smartphone operating systems, only Android users were selected for this study. The nature of data collection through smartphones, based on an app, means that data collection was beyond our immediate control, leading to exclusion of certain participants or missing data (e.g., due to a low battery preventing the app from recording and/or sending data).

Lastly, we acknowledge that this study was conducted through a non-clinical sample, recruited largely in a higher education environment. We thus would not infer that the smartphone usage levels and/or SAS scores indicate any impairment of everyday functioning.

4.6 Conclusion

We have assessed the efficacy of a new approach to monitoring user activity for the detection of problematic smartphone behaviour, by considering all the UI interactions made by a user. As compared to other measures, this directly engages the potential problematic physical behaviour as a signal. This approach also allows for a focus on exclusively active rather than active and passive smartphone activity. Our data indicates that the time a smartphone is active may not be a significant correlate of problematic behaviour, which is symptomatic of the smartphone being used for an increasingly wide variety of applications. Within heavy and diverse usage, a more detailed analysis of behaviour allows the potential sources of addiction to be better understood. Scrolling behaviour in particular, is worthy of further investigation.

Through this approach, using an exploratory study, we have been able to analyse indicators of SA across a sample of smartphone users ($N = 64$) over a period of 8 weeks. This has identified that SA is associated with the usage of Lifestyle and Social applications. We have also discovered that Snapchat, one of the most popular social media applications in use today, may be particularly indicative of problematic smartphone usage, indicated across all types of UI interactions. To date, few academic studies have identified such issues and this is worthy of further consideration, particularly given the significant usage of Snapchat by teenagers. Preliminary analysis of the Snapchat app, compared to other social media, leads us to hypothesise that the app's design provides a particularly strong pathway towards SA. This is further investigated in Chapter 5.

In summary, this chapter has made the following contribution (see Section 1.5) to this thesis:

C3 Analysis of predictors of SA: identification of smartphone usage behaviours that may contribute to SA and validation of UI interaction events as useful proxy for smartphone usage behaviours.

Chapter 5

User Interactions and Snapchat

Parts of this chapter have been presented at the UbiComp workshop AppLens and published in the peer-reviewed proceedings of the conference:

Beryl Noë, Liam D Turner, and Roger M Whitaker. Smartphone interaction and survey data as predictors of snapchat usage. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers*, pages 438-445. ACM, 2019.

In the previous chapter, in contrast to other smartphone apps, Snapchat was found to be highly correlated to SA. This prominent finding lead to a further investigation of the app, its characteristics and user interactions with it. As a highly popular social app, it is characterised by its unique way of making messaging a series of spontaneous experiences through the ephemeral, self-deleting pictures and videos sent as chats. In this chapter, we examine the predictors of Snapchat usage based not only from smartphone-user interaction, but also from data collected through surveys conducted with users (particularly, user mood and SA score). This chapter thus links to all 3 of the main themes of this thesis: mood, SA, and human-smartphone interaction. The identified predictors may be useful indicators of potential problematic behaviour linked to SA and inform campaigns and interventions aiming to prevent SA or curb Snapchat usage.

5.1 Introduction

Since its inception in 2011, Snapchat has allowed users to communicate through self-deleting pictures and videos and has quickly grown to be one of the most popular social media platforms. In 2016, users watched collectively some 10 billion videos per day [178] and in 2019, it has 190 million daily active users, ranking 4th in the list of most downloaded social media apps in the US [170]. Snapchat is particularly popular amongst young adults and teenagers [179, 77]. To a lesser extent, this is also the case for Instagram and Twitter, while Facebook attracts users from a much wider range of ages [153].

As with other popular social media sites such as Facebook, Instagram, and Pinterest, Snapchat has a female-skewed user-base. Pew Research Center [153] reports for 2018, that in the US, 23% of men and 31% of women declared using Snapchat. Differences in usage have been also observed, with Thelwall and Vis [187] finding that men were more likely to share images on Twitter while women preferred to use Snapchat. This trend was the same for posting frequency. Women were also more likely to add filters and text to their picture and video messages (*Snaps*) than men. The authors also noted that females took more screenshots and were more likely to upload Snaps to other social media platforms. In general, female users have been reported to have more concerns about online privacy and taking more measures to protect it [19].

With its short-lived, automatic deletion of Snaps, Snapchat uses not only spontaneity, but also privacy as a key selling point to attract users. This is apparent in a number of aspects. For instance, Snapchat user profiles reveal very little information, being limited to a username and profile picture. Snaps are also private and self-deleting, and Snapchat will notify the user if their interaction partner takes a screenshot of a Snap they sent, making them aware of it living on beyond its planned expiry. While Snaps are private and can only be seen by people the user directly sends them to, pictures and videos they upload on their *Story* are linked to their profile and can be seen by a wider audience. However, the app gives the user complete control over who can view this content. Snapchat's perceived privateness allow users to feel in control of the sensitive information they choose to disclose to friends. This has consequences for how the app is used by its user base. For instance, Utz et al. [197] have reported that about half of their participants had shared drunk photos and between an eighth and a fifth had engaged in sexting.

Snapchat's private atmosphere is also shown through an emphasis on maintaining contact with friends through the incentive of collecting and upgrading friend emojis that act similarly to reward badges for achievements in games. Piwek and Joinson [156] note that while Facebook is used more for *bridging* social capital (i.e., keeping weak links by communicating with a large network), Snapchat is used more for *bonding* (i.e., keeping strong links by communicating with a small network). Perceived closeness between interaction partners was found to be significantly higher for Snapchat than for other popular social media (Facebook, Twitter, Instagram), and even face-to-face conversation in research by Bayer et al [20]. Finally, differing audiences also shape the way users communicate. Choi and Sung [41] report that Snapchat users use Snapchat for the expression of their true and actual self, while Instagram is employed for the expression of their ideal self.

5.1.1 Motivation and Contribution

Due to the distinctive functionality and design of Snapchat, it offers features that may appeal to particular types of user who can benefit from the interpersonal "bonding" that Snapchat may provide [156]. However, the characteristics of such users is not yet well understood - and potentially complex to assert. There are many factors that mediate app usage [194], such as individual differences, context, other app usage and social influence, however the extent of these in predicting Snapchat usage has not been determined in detail.

In this chapter, we seek to contribute new knowledge to understand predictors of

Snapchat usage by assessing the users' disposition in a number of dimensions: through questionnaires and user behaviour quantified by interactions with the smartphone. This combination of techniques offers a broad range of potential indicators relative to both stable characteristics (e.g., a user's disposition) as well as behaviours detected through the smartphone in real time (e.g., interactions with the interface). The result is a comprehensive and multi-dimensional approach to identifying predictors of Snapchat usage. To the best of our knowledge, this has not been previously undertaken.

5.2 Methods

Data analysed in this chapter was collected through the *Tymer* application and through surveys held during the briefing session. How this data was collected is described in more detail in Section 2.2.

Specifically, we use the following data sources:

- Demographics data: gender, age
- Survey data (briefing):
  - SA score
  - BFI scores
  - MCQ score
  - Sleep: quantity and quality
- Smartphone usage data:
  - Type of data: Human-smartphone interaction events (taps, long taps, scroll, writing, selection)
  - Sources of data: Snapchat and other specific apps (e.g., Facebook Messenger, Facebook, WhatsApp, WeChat, YouTube, Instagram, Google Play Store, Google Calendar)

- Mood data: DM

As in Chapter 4, the number of interaction events was used as a measure of app usage rather than time between app launches and switching apps or screen locking. This was done to consider active usage only. Only app usage and no other forms of smartphone usage were analysed in this chapter as independence of observations for all variables needed to be maintained. An overview of the usage of the Snapchat app for all participants is shown in Figure 5.1.

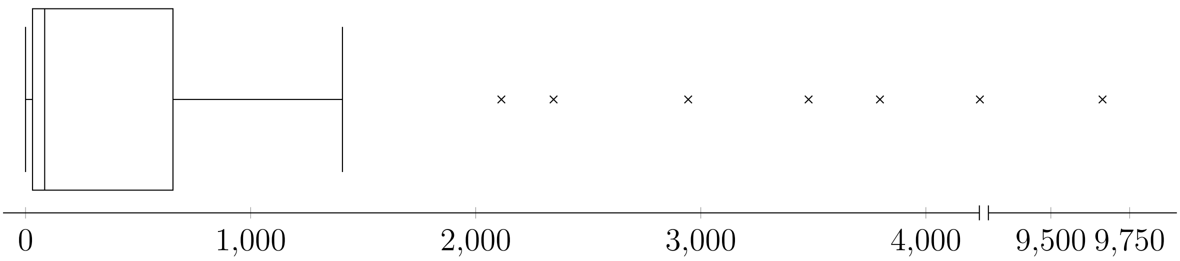


Figure 5.1: Daily number of Snapchat usage events, $N = 64$

With regards to mood, we only considered DM reports which participants were prompted to answer once per day in the evening as a summary of how they felt prevalently during the day. Participants had the choice between the following options: Tense, Excited, Happy, Relaxed, Calm, Bored, Upset, Stressed, and Neutral. An overview of average frequency of reported moods is given in Section 2.3.2. For each participant, a score for each mood was obtained by dividing the number of occurrences of this mood by the total number of daily mood reports accumulated over the total duration of the study. Although subject to memory biases (see Chapter 3), a daily measure for mood was preferred for this study over the use of shorter intervals to take into account the mood the participant found most representative for their day and avoid the need to use both mood and intensity measures.

5.2.1 Data Analysis

To find predictors of Snapchat usage, survey data alone was first considered, followed by app interaction data alone, and finally, both types of data were analysed together.

Multiple regressions were performed with a log-transformed Snapchat variable so the parametric test could be used. The residuals of the regression were tested for normality using a Predicted Probability (P-P) plot. Homoscedasticity was tested by evaluating a scatter plot of the predicted values by the residuals and the Breusch-Pagan test. Multicollinearity was tested by evaluating the Variance Inflation Factor (VIF); variables with a VIF higher than 10 were excluded. No assumptions were violated.

Consistent with previous reports [153, 77], female participants in our sample ($M = 1157.03, SD = 2041.75$) used Snapchat significantly ($Z = -2.677, p = .007$) more than men ($M = 264.81, SD = 506.77$) on a daily basis and age had a high negative association with Snapchat usage ($r = -.467, p < .001$), therefore the demographic variables gender and age were considered confounding factors.

In order for the regression model to take these variables in account, a forced entry model regression was therefore used with a hierarchical structure where gender and age were inserted as a first block in the analyses using survey data. Further variables were also divided in subgroups (blocks), allowing for evaluation of the contribution to the predictability of several variables at once.

To determine in what order these should be entered into the forced entry model, a backward elimination regression was first performed. The order in which the variables were deleted from the backward elimination model regression was the reverse order they were entered (in blocks of 2 to 6 variables) into the forced entry model regression. Model 1 subsequently consisted of block 1, model 2 of block 1 and 2, and so forth. The full list of variables and entry blocks can be found in the Appendix A.2. Only the results of the model with the best fit (i.e., lowest Bayesian Information Criterion (BIC) value [130]) are reported in this study.

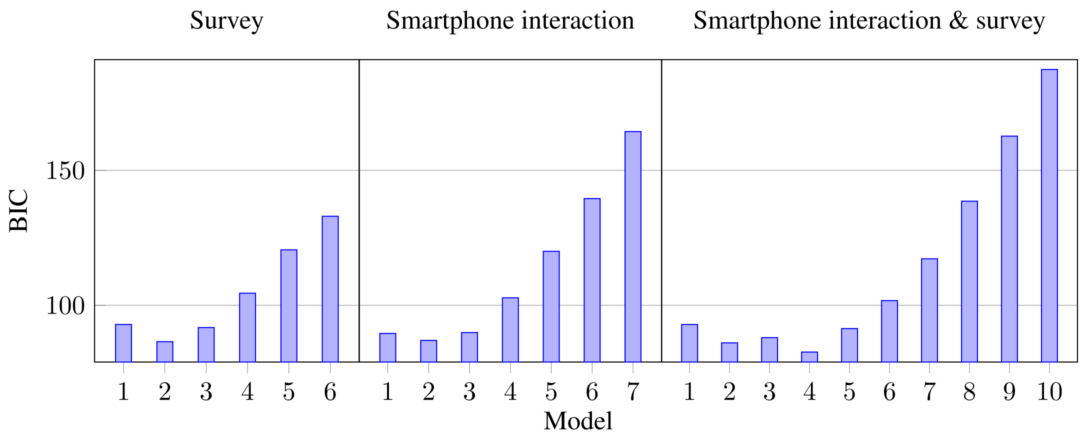


Figure 5.2: Bayesian Information Criterion (BIC) values for each model.

5.3 Results

5.3.1 Survey Data as Predictors of Snapchat Usage

The model that could most accurately predict Snapchat usage based on survey data according to the Bayesian Information Criterion values was model 2 (comprised of blocks 1 and 2) with a BIC value of 86.539 and a R^2 value of .424 (see Figure 5.2). The control variable gender was not a significant predictor for Snapchat use. However, age, Smartphone Addiction score, feeling bored, and feeling happy were significant predictors for Snapchat usage. More details can be found in Table 5.1.

5.3.2 Smartphone Interaction Data as Predictors of Snapchat Usage

The model that could most accurately predict Snapchat usage based on app usage data was model 2 (comprised of blocks 1 and 2) with a BIC value of 86.991 and a R^2 value of .383 (see Figure 5.2). All variables were significant predictors for Snapchat usage: WhatsApp, Facebook Messenger, Instagram, and BBC News, and Messaging. More details can be found in Table 5.2.

Table 5.1: Regression results for model 2 for the relationship between Snapchat usage and survey data.

Predictors	β
Smartphone Addiction	.341**
Happy	.248*
Boredom	.255*
Age	-.346**
Gender	.179
Model statistics	
BIC	86.539
ANOVA	F (57,5) = 8.389***

†p<.10, *p<.05, p**<.01, p***<.001

Table 5.2: Regression results for model 2 for the relationship between Snapchat usage and smartphone interaction data.

Predictors	β
WhatsApp	.449***
Facebook Messenger	.352**
Instagram	.236*
BBC News	-.227*
Model statistics	
BIC	86.991
ANOVA	F(59,4) = 9.157***

†p<.10, *p<.05, p**<.01, p***<.001

5.3.3 Smartphone Interaction and Survey Data as Predictors of Snapchat Usage

Google Music, Google Keep, Bored, Relaxed, and Sleep quality were excluded from the analysis due to multicollinearity with other variables.

Table 5.3: Regression results for model 4 for the relationship between Snapchat usage and the smartphone interaction and survey data.

Predictors	β
Age	-.657***
Gender	-.124
WhatsApp	.406***
BBC News	-.365***
Smartphone Addiction	.411***
Gmail	.334**
Wake up frequency	-.214*
Sleep amount	-.209*
Amazon Shop UK	.172†
Conscientiousness	.219*
Facebook Messenger	.199*
Happy	.188*
Model statistics	
BIC	82.685
ANOVA	F(50,12) = 8.018***

†p<.10, *p<.05, p**<.01, p***<.001

The model that could most accurately predict Snapchat usage based on app usage and survey data was model 4 (comprised of blocks 1, 2, 3 and 4) with a BIC value of 82.685 and a R^2 value of .658 (see Figure 5.2). All variables except gender and Amazon Shop UK were significant predictors for Snapchat usage: age, WhatsApp, Facebook Messenger, BBC News, Smartphone Addiction score, Gmail, wake up frequency, amount of sleep, Conscientiousness and feeling happy. More details can be found in Table 5.3.

5.3.4 Overview

All significant predictors had a positive relationship with Snapchat usage, except age, BBC News app usage, wake up frequency and amount of sleep which were negatively associated with interactions with the Snapchat app. Table 5.4 shows an overview of these results.

Table 5.4: Significant predictors for Snapchat usage based on survey data, smartphone use data, and both. *Italics* indicate a negative association.

Type of data	Survey	Smartphone use	Survey and Smartphone use
Demographics	*Age*		*Age*
Addiction	Smartphone Addiction		Smartphone Addiction
Mood	Happy		Happy
	Bored		
Sleep	-		*Wake up frequency*
			Sleep amount
Personality	-		Conscientiousness
Apps		WhatsApp	WhatsApp
		Facebook Messenger	Facebook Messenger
		BBC News	*BBC News*
		Instagram	Gmail

5.4 Discussion

In this chapter, we have identified predictors of Snapchat usage based on both passively collected smartphone interaction events and user surveys. The methodology that we have used then combined both approaches to determine which predictors were most important overall. It is worth noting that most of the significant predictor variables in the first two analyses recurred in the final analysis. Furthermore, while none of the variables relating to personality or sleep were found to be predictors of Snapchat usage when looking at survey data only, they were relevant when considered together with smartphone interaction data.

Although gender effects have been reported in previous studies [18, 156, 187] and we found a significant difference in usage levels with women interacting significantly more with Snapchat than men, gender does not appear to be a significant predictor for Snapchat use in our sample. In contrast to gender, age was consistently a significant predictor for Snapchat usage with a high beta weight. The importance of age as a predictor is consistent with reports of the popularity of the app amongst young adult and teenage age groups while being sparsely used in older generations. This phenomenon reflects also the faster speed at which young people adopt new social media and new technology [115]. This plays a particularly large role for Snapchat as it is only available as an app, contrary to other popular social media such as Facebook, Instagram and Twitter which can be accessed as websites on other devices as well.

The use of social media has been linked to smartphone addiction in the wider literature [25, 161, 165, 168] and we have identified Snapchat use as a particularly strong correlate in the previous chapter. It is therefore unsurprising that this relationship comes forward again in this study. As a type of behavioural addiction, smartphone addiction is an indicator of dependence for users that experience using their phones as rewarding despite it resulting in negative consequences on their health, social relationships and/or other aspects of their lives [53].

We have also identified that interactions with several other apps are predictors for the use of Snapchat. WhatsApp, Facebook Messenger, Gmail and Instagram were positive predictors, while the BBC News app was linked negatively to Snapchat usage. WhatsApp and Facebook Messenger are the two most popular chatting apps worldwide. As a notable part of Snapchat's functionality surrounds chatting (with pictures), it is not unexpected that high levels of communication using these apps are predictors of high interaction with Snapchat. The email client Gmail is also arguably a communication app. It differs from either of the 3 previously mentioned apps in several aspects and thus makes for a more unexpected predictor of Snapchat use. While chats are a generally casual way to interact with friends and family through short messages, emails are commonly longer and used more in professional, educational, or generally formal settings where conversation partners are not necessarily close to each other [20]. It thus starkly contrasts with Snapchat, which could be described as the opposite in many aspects. We posit that it therefore serves a complementary function rather than being a predictor of Snapchat use due to its similarity with the app.

Waking up less frequently during the night was a significant predictor for Snapchat use. This is perhaps surprising as the app pushes towards more increased user engagement through notifications and gamification elements aimed at pairs of users maintaining a minimum snapping frequency. However, sleeping less was also a predictor of Snapchat use. This finding is consistent with results of Mark et al. [128], who examined Facebook usage in relation to sleep and attention. They proposed sleep debt as a possible cause of increased Facebook usage, as sleep deprived individuals would seek out activities requiring a lower cognitive cost, such as social media use.

Conscientiousness was a significant positive predictor of Snapchat use. This finding is of interest as the literature has been inconsistent concerning its link with social media use: both negative [91, 101] and positive associations have been reported [147].

In our analysis, no correlation is found between Conscientiousness and Snapchat usage ($r = .004, n.s.$). As a significant predictor of Snapchat usage, this means that it could play a moderating role rather than influencing Snapchat usage directly. This would be consistent with the findings that conscientious individuals tend to refrain from using social media [166], but if they do, they show consistency in their behaviour. Similarly, research examining check-in behaviour on Foursquare, a location based social network app, found a weak correlation with Conscientiousness, which the authors attribute to diligence and persistence, key characteristics of this personality facet [42]. On Snapchat, perseverance is also required: notably to maintain *Snapstreaks* scores by snapping back and forth with friends at least once per 24 hours. This result is worthy of further examination.

Lastly, Snapchat use was positively predicted by both high number of reports of daily happiness and boredom. In their examination of motivations for usage of a number of social media platforms, Alhabash & Ma [6] note that the primary reason behind Snapchat use is entertainment, followed by convenience, medium appeal and passing time. Vaterlaus et al. [201] have reported that when asked what type of content they shared on Snapchat, 98.7% of the user group they surveyed responded they sent “funny things”. Snapchat therefore seems to be a prominent go-to app when experiencing boredom and might be successful in eliciting positive emotions in users.

5.5 Conclusion

Examining both survey and smartphone interaction data, we have identified significant predictors for Snapchat usage. We found significant demographic (age) and behavioural (Smartphone Addiction score) predictors, but also predictors relative to sleep (sleep amount and wake up frequency), mood (happiness and boredom), personality (Conscientiousness), and app interaction (WhatsApp, Facebook Messenger, BBC News, Instagram, and Gmail). These findings highlight the unique usage behaviours associated with the app and complement observations in Chapter 4 which sets Snapchat apart from other social media applications. Our findings reveal some novel predictive variables which have not previously been linked to Snapchat usage. These may be useful in interventions for problematic Snapchat and smartphone usage.

Towards future work, further investigation of Conscientiousness as a possible moderating factor would be worth pursuing to determine under what circumstances the personality facet that is usually characterised by low social media use is positively associated with Snapchat usage.

This chapter constitutes the following contribution (see Section 1.5) to this thesis:

C4 Analysis of predictors of Snapchat usage: identification of demographic and behavioural factors characteristic of Snapchat usage.

Chapter 6

User Interactions and Mood

Inferring an individual's mood has been a point of interest in both Psychology and Computer Science, with research topics ranging from the recognition of facial affect [60] to the sentiment analysis of Tweets [2]. In this chapter, we are interested in uncovering associations between smartphone usage behaviours and subsequent mood reports. We assess the predictive capability of UI interaction data for the inference of both mood valence and arousal. Two of the main themes of this thesis are therefore covered here: mood and smartphone-user interaction.

Together with the findings reported in chapters4 and 5, the results presented here may be useful in informing interventions for mood improvement and may help users gaining more awareness of the impact of their smartphone usage habits on their mood and well-being, also enabling them to make more informed app usage choices.

6.1 Introduction

Mood influences human behaviour. This is not only apparent in someone's body language, facial expression and tone of voice, but also can be reflected in how someone acts. Indeed, positive affect has been linked to faster decision making [93], but also a greater interest in participating in a wide range of activities, while negative mood may deter from engaging in social, leisure and strenuous activities [48]. Additionally, anxious people are found to be more risk averse [37], while anger in men [70] and leisure boredom in adolescents has been associated with higher taking behaviour [209]. Overall, emotional events are also remembered more precisely and for a longer time than neutral events [196].

In this chapter, we are interested specifically in how mood is reflected in smartphone usage behaviour: what applications users are more likely to use while experiencing a negative mood or what usage patterns users might display when aroused?

6.1.1 Related Literature and Hypotheses

Previous literature has foremost focused on the health risks associated with smartphone use, particularly excessive use as typically experienced with SA. In these studies, mobile use has notably been linked to stress (e.g., [39, 40, 207]), anxiety (e.g., [169, 118, 65]) and depression (e.g., [214, 7, 54]). *This points to supporting the hypothesis that periods of high overall usage are negatively associated with mood valence (H1)*, i.e., when users use their phones more, they are more likely to report negative moods such as “bored”, “upset”, and “stressed”.

Investigating more precise usage behaviours, Kushlev and colleagues [106] reported that checking emails less frequently reduced participants’ daily amounts of stress. *We therefore hypothesise that UI interactions with work related apps such as email and calendar apps are negatively associated with mood valence and positively associated with mood arousal (H2)*, i.e., when users use email and calendar apps more, they are more likely to report being “stressed”.

In their review, Appel and colleagues [14] highlighted that especially passive Facebook use was correlated with unfavourable social comparisons and envy, which mediated depressed mood. FoMO has been a topic of interest for its mediating influence between social media use and smartphone addiction. Past literature that have studied this phenomenon have notably linked it to a wide range of negative moods, including depression, anxiety, stress, and boredom [62, 92, 108]. *We therefore predict that UI in-*

teractions on apps of the Social app category, and in particular reference to Facebook, Instagram, Snapchat, and Twitter are negatively associated with mood valence (H3), i.e., users who are more active on social media apps are more likely to report feeling “bored”, “upset”, and “stressed”.

While investigating boredom in smartphone users, Matic and colleagues [131] found that the number of social network notifications, the frequency of checking notifications, and changes in screen status to be the strongest predictors for boredom, which is characterised by failures of attention engagement [58]. Based on these previous observations, we hypothesise that *the frequency of switching between applications is negatively associated with both mood valence and arousal (H4)*, i.e., users who switch more frequently between applications are more likely to report feeling “bored”. Additionally, we expect an increased scrolling behaviour in bored users: Scrolling typically requires the least precision in finger positioning in comparison to taps, writing, or text selection and is used in many applications that feature unending feeds (e.g. Twitter) to provide more content. This type of behaviour seems congruent with inattentive individuals. We therefore hypothesise that *scrolling events are negatively associated with both mood valence and arousal (H5)*, i.e., users who use an increasing number of scroll movements while interacting with their phone are more likely to report feeling “bored”. The need to be entertained and boredom have moreover been reported to be the second and third most cited reasons to visit the app store according to research By Lim and colleagues [123]. This seems to support the hypothesis that *UI interactions within the Google Play Store app are negatively associated with both mood valence and arousal (H6)*, meaning that we expect users who interact more with the Google Play Store app to report feeling “bored” more.

Relationships with social contacts such as family and friends are central when considering subjective well-being or happiness [137, 116, 15]. We therefore expect that smartphone usage characterised by maintaining these close connections, such as texting and chatting through apps like WhatsApp and Facebook Messenger is associated with reports of positive moods such as “happy”, “excited”, and “relaxed”, leading to the hypothesis that *UI interactions on apps of the Communication app category, and in particular reference to WhatsApp, Facebook Messenger, Hangouts, and WeChat are positively associated with mood valence (H7).* Along with “Social contacts with friends, or others in close relationships”, Argyle and Martin [15] list “Nature, reading, music” as one of the 7 main causes of joy. In their ESM study following American adolescents for a week, Csikszentmihalyi and Hunter [47] identify passive leisure activities such as watching movies and listening to music as being linked to reports of above average happiness. In accordance to these findings, we hypothesise that *UI interactions on apps of the Entertainment, Music and Video player app categories, and in particular reference to YouTube are positively associated with mood valence (H8)*, i.e., higher usage of Entertainment, Music and Video player apps is observed concurrently with reports of “happy”, “excited”, and “relaxed” moods.

Lastly, past literature has reported of users reverting to playing games when stressed or bored as means to unwind or to seek arousal [133]. Certain game design elements such as music [85] and difficulty [186] might further contribute to heightened arousal. We therefore hypothesise that *UI interactions on apps of the Game category are positively associated with mood arousal (H9)*, i.e., users may report feeling more “stressed”, “tense”, or “excited” after playing games on their phone.

6.1.2 Summary of Hypotheses

A summary of all hypotheses is given below and has been represented graphically in accordance to the Circumplex Model of Affect [164] in Figure 6.1.

> *H1:* Overall usage is negatively associated with mood valence.
>
> *H2:* UI interactions with work related apps such as email and calendar apps are negatively associated with mood valence and positively associated with mood arousal.

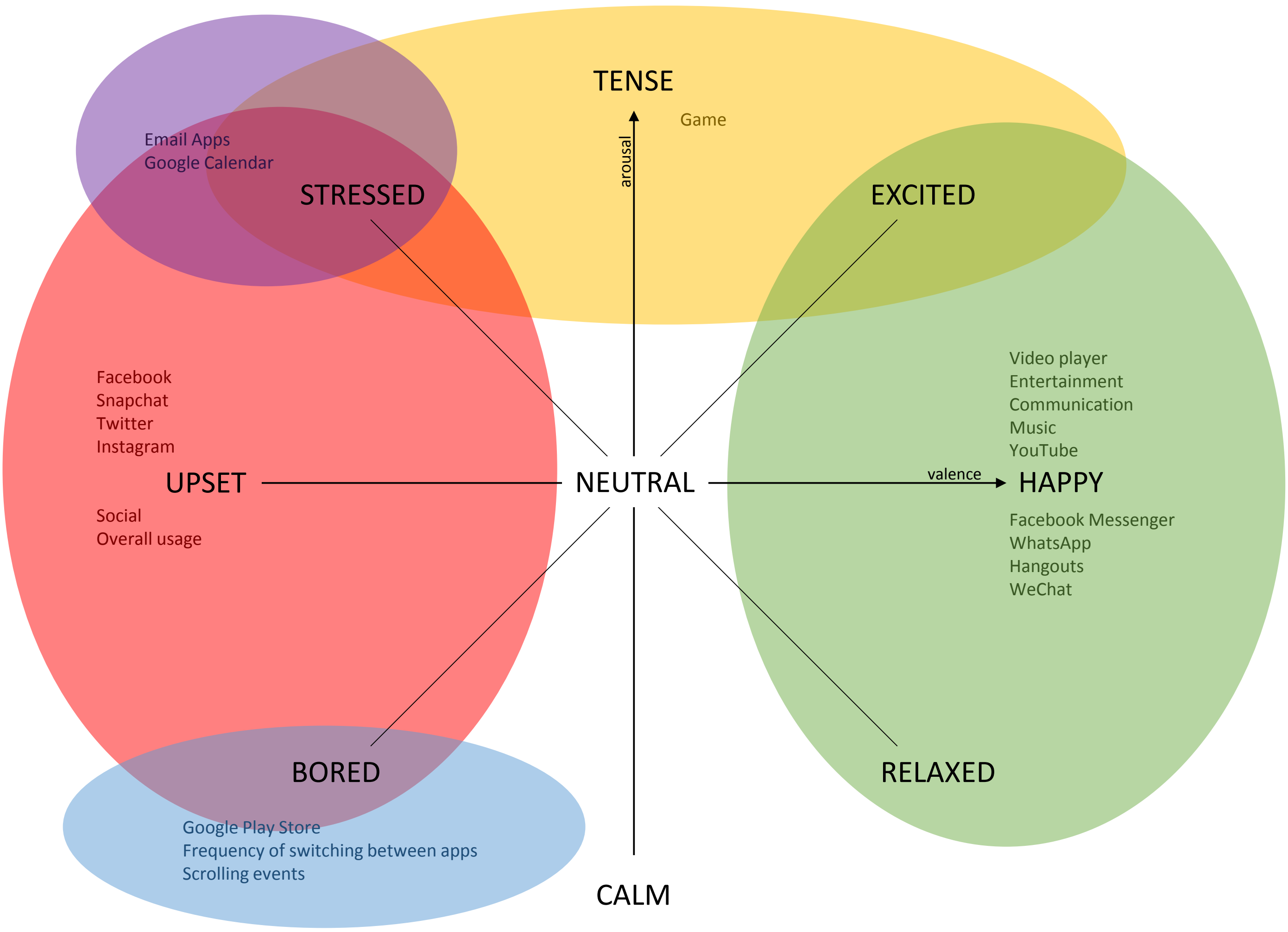


Figure 6.1: Hypotheses: Expected positive associations.

H3: UI interactions on apps of the Social app category, and in particular reference to Facebook, Instagram, Snapchat, and Twitter are negatively associated with mood valence.

H4: The frequency of switching between applications is negatively associated with both mood valence and arousal.

H5: Scrolling events are negatively associated with both mood valence and arousal.

H6: UI interactions within the Google Play Store app are negatively associated with both mood valence and arousal.

H7: UI interactions on apps of the Communication app category, and in particular reference to WhatsApp, Facebook Messsenger, Hangouts, and WeChat are positively associated with mood valence.

H8: UI interactions on apps of the Entertainment, Music and Video player app categories, and in particular reference to YouTube are positively associated with mood valence.

H9: UI interactions on apps of the Game category are positively associated with mood arousal.

6.2 Methods

Data analysed in this chapter was collected through the *Tymer* application. How this data was collected is described in more detail in Section 2.2.

To assess user mood based on user behaviours, we use the following data:

- Demographics data: gender, age
- Smartphone usage data:
  - Type of data: Human-smartphone interaction events (taps, long taps, scroll, writing, selection)
  - Sources of data: all apps, specific app categories (Social, Communication, Music, Video Player, Entertainment), specific type of apps (email apps), specific apps (Facebook Messenger, Facebook, WhatsApp, WeChat, YouTube, Snapchat, Instagram, Google Play Store, Google Calendar)
- Mood data: CM, DM

In this chapter, we assess mood under different participant response mechanisms, therefore two studies were conducted. In both cases, the number of data points was caped at 56 days. When two or more mood surveys were filled in within a certain time frame (1h for CM and 1 day for DM), only the first survey was retained. Surveys that were not filled in were disregarded. Participants who had less than one third of the expected data points were removed from the analysis.

For Study 1, 51 participants were retained with 5630 CM surveys in total, with an average of 110.39 (SD = 35.89) surveys. For Study 2, 61 participants were retained with 2635 DM surveys in total, with an average of 43.92 (SD = 10.03) surveys.

6.2.1 Data Transformation

To be able to analyse the data using multilevel mixed effects linear regressions models, the mood variables in particular had to be transformed as the categorical nature of these doesn't lend itself as well to the application of these intended analyses. Due to being derived from the Circumplex Model of Affect [164], which assumes two dimensional coordinates for all moods, we could translate the categorical values into continuous ones, including the intensity measure for CM reports too. Similarly, smartphone usage had to be quantified though the use of UI interaction events, as was done in Chapter 4.

Mood Data

Current moods were collected through CM surveys, where participants could chose between 8 moods ("excited", "happy", "relaxed", "calm", "bored", "upset", "stressed", "tense") with 3 levels of intensity ("lightly", "moderately", "strongly") and "neutral". The same choices were available for DM surveys, except no option of intensity measure was given. This resulted in a categorical variable for mood and an ordinal variable for intensity.

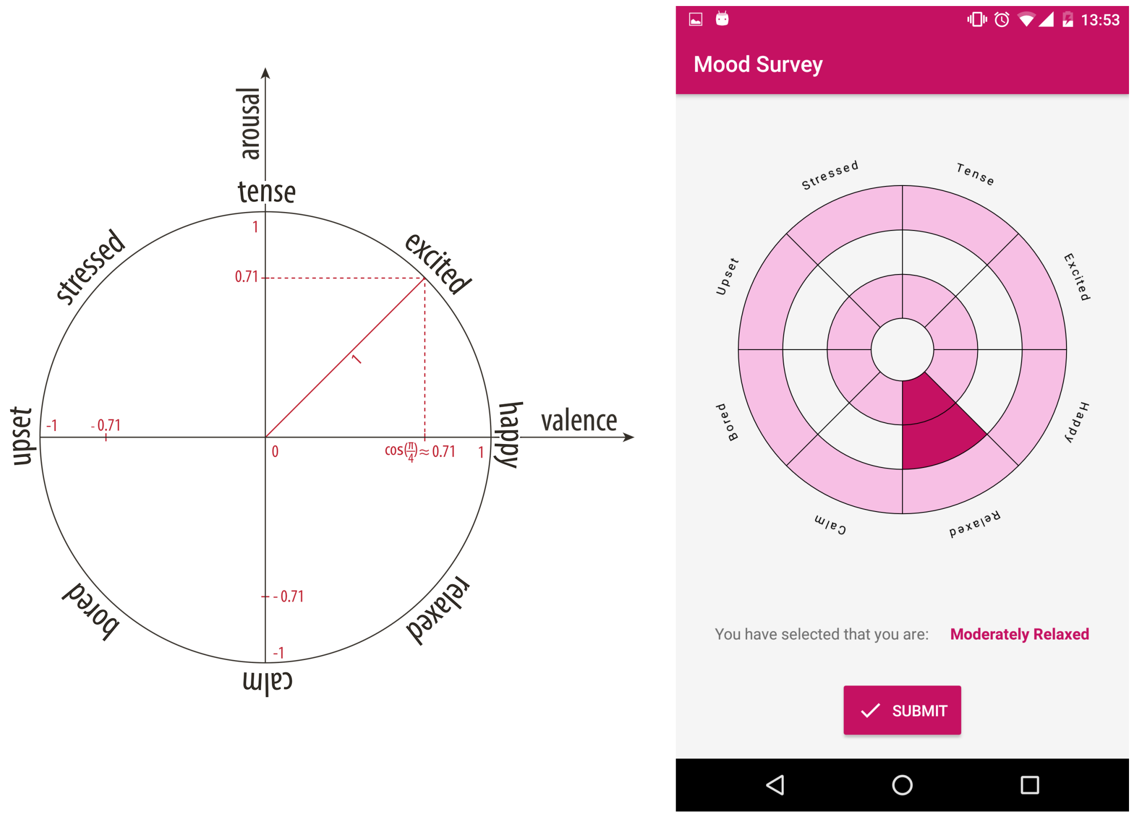


Figure 6.2: Placement of all used moods on the Circumplex Model of Affect (left) in comparison to the interface for CM reports on *Tymer* (right).

According to their coordinates on the Circumplex Model of Affect [164] (see Figure 6.2), each mood label was translated into a valence and arousal value as seen in Table 6.1). For CM surveys, these values were multiplied by the reported intensity: $\times 1$ for "lightly", $\times 2$ for "moderately", and $\times 3$ for "strongly". This resulted in the translation of the mood (and intensity) variable into two new continuous variables: valence and arousal.

6.2.2 Smartphone Interaction Data

In this chapter again, the number of interaction events (taps, long taps, writing, text selection, and scroll) was used as a measure of smartphone usage activity. Levels of activity over all apps, specific app sources, or interaction behaviours were calculated

Table 6.1: Translation of mood labels to arousal and valence values according to the Circumplex Model of Affect [164] shown in Figure 6.2.

	Valence	Arousal
Tense	0	1
Excited	0.71	0.71
Happy	1	0
Relaxed	0.71	-0.71
Calm	0	-1
Bored	-0.71	-0.71
Upset	-1	0
Stressed	-0.71	0.71
Neutral	0	0

for each mood report, CM and DM, for respectively 1h and 12h preceding the report.

For study 1, levels of activity were evaluated in 16 apps, groupings of apps, or interaction behaviours which were individually used as predictors to predict arousal and valence in CM reports respectively. All predicting variables used were: overall usage, app categories (Communication, Game, Music, Social and Video Player), a grouping of email apps, individual apps Facebook, Facebook Messenger, Instagram, Snapchat, Twitter, WhatsApp, YouTube and the interaction behaviours scrolling and switching between apps. The number of these variables was limited to popular apps and app categories which had at least 5% of non-zero values for the activity measure over all associated CM reports. For study 2, 4 more apps (Hangouts, Google Calendar, Google Play Store, WeChat) and 1 more app category (Entertainment) were added to the analysis as the 5% cut-off did not exclude them for the analysis regarding DM.

6.2.3 Data Analysis

In this chapter, we seek to predict arousal and valence based on smartphone usage. Due to interpersonal differences, the analysis needs to take into account the interaction between the longitudinal measures of mood and the longitudinal measures of usage data per participant. This longitudinal nature and hierarchical structure of the data is shown in Figure 6.3. This increases the complexity and requires multilevel modelling in order to disregard individual differences between participants, i.e., associations needed to be considered over time at an individual level so the general trend for all users could be evaluated. Multilevel mixed effects linear regression models were therefore fitted using the nlme package in R [155]. Random intercepts and fixed slopes were used. The model also took into account auto-correlation between consecutive data points of the same participant using the corCAR1 class (on an hour level) from the same package. This was done to remove the effects that a previously recorded mood could have on a subsequently recorded mood.

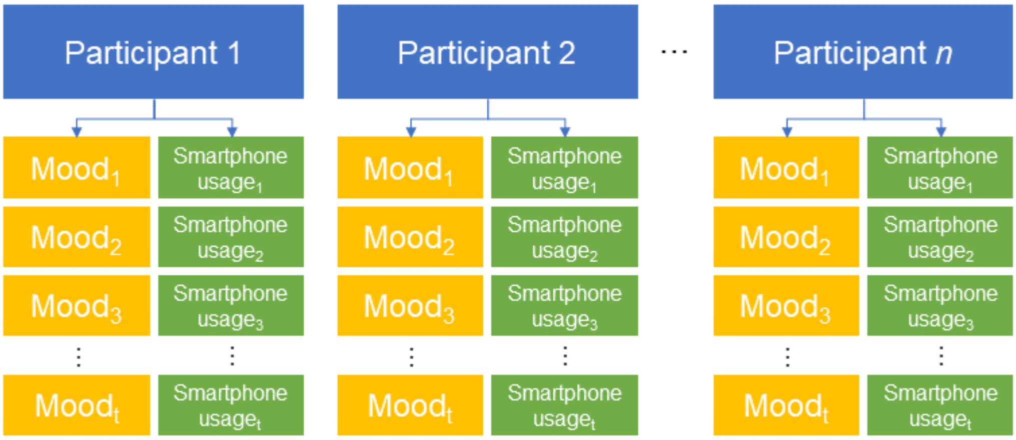


Figure 6.3: Multilevel structure of mood and smartphone usage data.

Both age and gender were assessed as confounding variables. While age did not have any significant impact on the prediction of mood, it was found that men ($Mdn = -0.71$) reported significantly ($p < .01$) more low arousal daily moods than women

($Mdn = 0$). This effect was not found for CM reports however. The distribution for DM reports per arousal level for each gender can be seen in Figure 6.4 (the same graph for CM reports can be found in Appendix A.3). Gender was therefore included as a predicting variable in all models seeking to predict DM.

The residuals were normally distributed for all analyses, therefore no further data transformation was needed. No assumptions were violated.

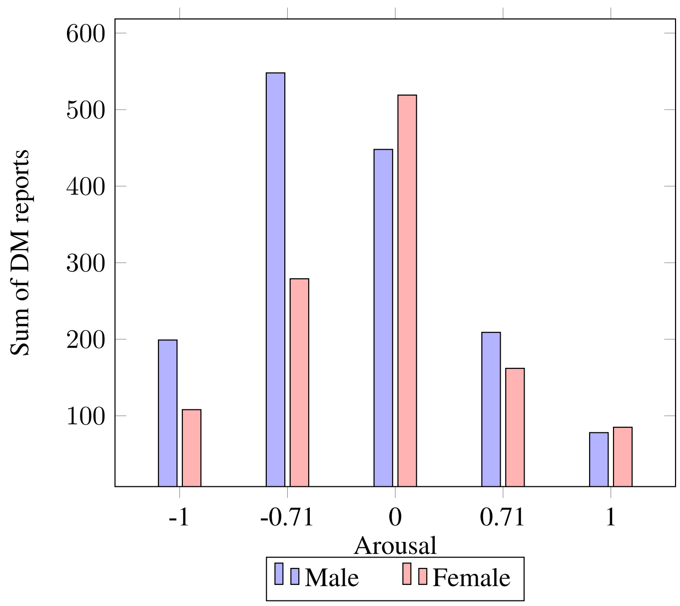


Figure 6.4: Sum of DM reports per arousal level per gender.

6.3 Results

Multilevel mixed effects linear regressions models were used to find associations between smartphone usage behaviours preceding CM and DM reports and the valence or arousal of the reported mood. Equations are given for each of the regression models that showed a significant association between the examined variables. It is worth noting that, due to the order of magnitude of UI events (e.g., approximately 20.000 UI events on a daily basis per participant, see Figure 2.5) and thus the little impact a single event such as a tap has, the values representative of the slopes are accordingly small.

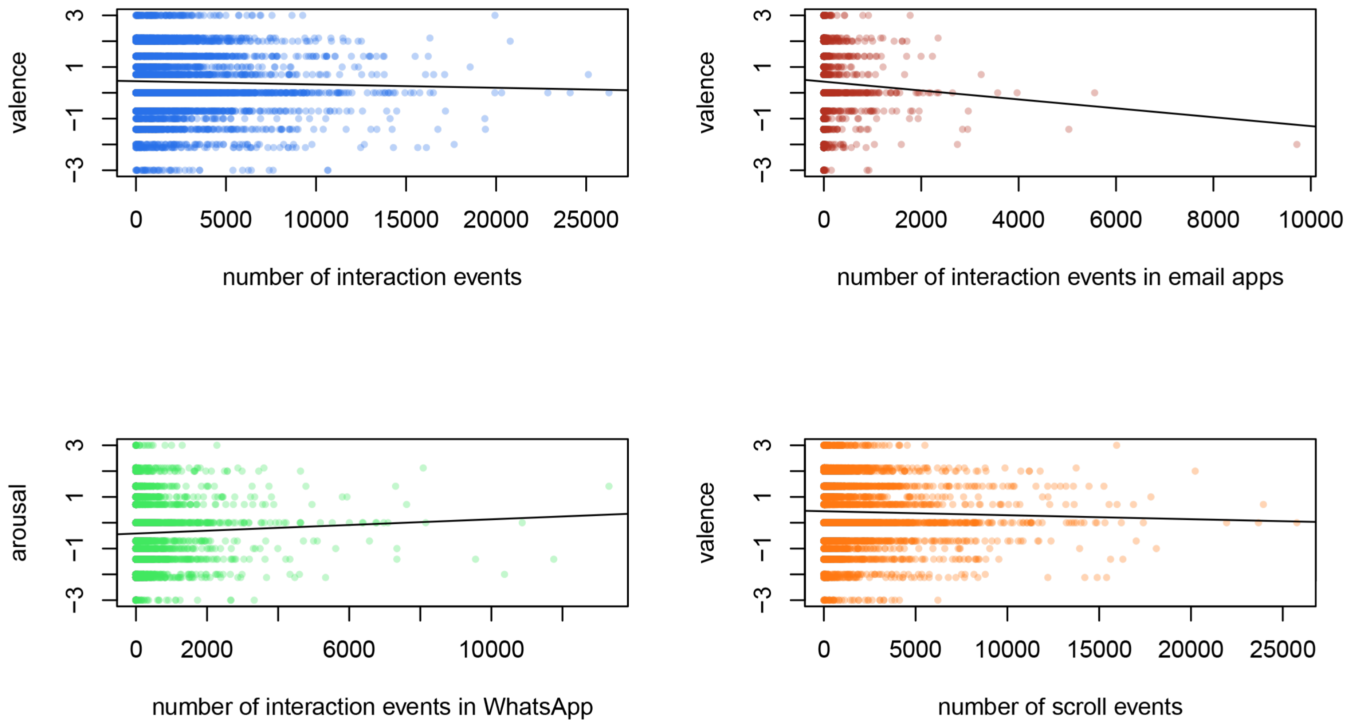


Figure 6.5: Regression models for prediction of Current Moods.

6.3.1 Study 1: Current Mood

Using the data collected in a time window of 1 hour preceding CM reports, 4 models that significantly predicted the outcome variable were found.

Firstly, increasing overall usage significantly ($p < .05$) predicted the reports of lower valence moods. The regression model can be described by the equation: $y = 0.4504647 - 0.0000128x$.

The same effect ($p < .05$) was found for scroll events, which constitute a big portion of the overall usage. The regression model for the prediction of valence by scroll events can be noted as following: $y = 0.4449624 - 0.0000154x$.

Email app usage too was found to be a predictor of lower valence mood with the regression model characterised by the equation: $y = 0.43304 - 0.0001722x$.

Finally, increasing interaction with the chatting and texting app WhatsApp predicted the reports of higher arousal moods. The regression model has in this case a negative intercept, meaning negative arousal is predicted for individuals in the absence of WhatsApp usage: $y = -0.4183225 + 0.0000551x$.

These regression models can all be found plotted in Figure 6.5.

Beta coefficients for all analysed predictor variables can be found in Table 6.2.

Table 6.2: Coefficients for multilevel mixed effects linear regression models predicting CM (valence and arousal) on the basis of smartphone app usage and interaction behaviours [β coefficients $\times 10^4$].

Predictor variables		Predicted variables	
		Valence	Arousal
Overall usage	Overall usage	**-0.128***	0.014
App categories	Communication	-0.070	-0.060
	Game	-2.466	0.554
	Music	2.614	1.135
	Social	-0.122	-0.040
	Video player	-0.642	0.373
Group of apps	Email apps	**-1.722****	0.519
Apps	Facebook	-0.231	-0.028
	Facebook Messenger	0.079	0.317
	Instagram	1.247	-1.363
	Snapchat	-0.056	0.521
	Twitter	-0.946	2.710
	WhatsApp	-0.061	**0.551***
	YouTube	-0.591	0.377
Type of behaviours	Scroll	**-0.154***	-0.076
	Switches	-1.568	1.351

†p<.10, *p<.05, p**<.01, p***<.001

6.3.2 Study 2: Daily Mood

Using the data collected in a time window of 12 hours preceding DM reports, 2 models that significantly predicted the outcome variable were found. Both of these models' predictors were scroll events: an increase in the number of scroll actions was linked to an increase in the reports of higher valence moods (i.e., "excited", "happy", and "relaxed"), described by the equation: $y = 0.29524494 + 0.00000328x$, and the decrease in the reports of lower arousal moods (i.e., "relaxed", "calm", "bored"), described by the equations $y = -0.23704769 - 0.00000331x$ for men and $y = -0.08836646 - 0.00000331x$ for women. Increasing numbers of scroll events predicting higher valence in DM reports is in contradiction with the findings found in the analysis of CM reports.

These regression models can all be found plotted in Figure 6.6. Beta coefficients for the remaining analysed predictor variables can be found in Table 6.3.

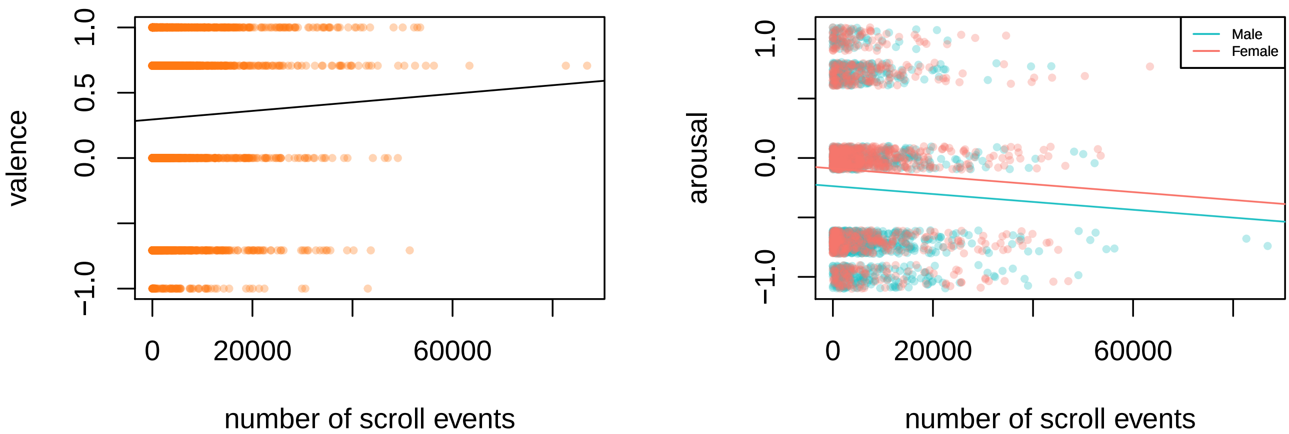


Figure 6.6: Regression models for prediction of Daily Moods (noise added to arousal values: 0.1).

Table 6.3: Coefficients for multilevel mixed effects linear regression models predicting daily mood (valence and arousal) on the basis of smartphone app usage and interaction behaviours with gender added as confounding factor for the prediction of daily arousal [β coefficients $\times 10^4$].

Predictor variables		Predicted variables: Valence	Predicted variables: Arousal
Overall usage	Overall usage	-0.023	-0.013
	Gender		**0.149****
App categories	Communication	-0.036	-0.017
	Gender		**0.149****
	Entertainment	0.024	-0.389
	Gender		**0.144****
	Game	0.461	-0.035
	Gender		**0.144****
	Music	0.202	1.175
	Gender		**0.141****
	Social	-0.037	-0.040
	Gender		**0.145****
	Video player	0.186	-0.475
	Gender		**0.145****
Group of apps	Email apps	-0.126	0.003
	Gender		**0.144****
Apps	Facebook	-0.031	-0.041
	Gender		**0.143****
	Facebook Messenger	-0.052	-0.081
	Gender		**0.147****
	Google Calendar	-1.975	-1.456
	Gender		**0.144****

Table 6.3: Coefficients for multilevel mixed effects linear regression models predicting daily mood (valence and arousal) on the basis of smartphone app usage and interaction behaviours with gender added as confounding factor for the prediction of daily arousal [β coefficients $\times 10^4$].

Predictor variables		Predicted variables: Valence	Arousal
Apps	Google Play Store	-0.497	-0.130
	Gender		**0.144****
	Hangouts	-0.007	0.213
	Gender		**0.144****
	Instagram	-0.799	-1.126
	Gender		**0.150****
	Snapchat	-0.017	-0.219
	Gender		**0.150****
	Twitter	-0.676	-0.245
	Gender		**0.145****
	WhatsApp	-0.096	0.040
	Gender		**0.140***
	YouTube	0.184	-0.469
	Gender		**0.145****
	WeChat	0.027	0.109
	Gender		**0.142****
Type of behaviours	Scroll	**0.033***	**-0.033***
	Gender		**0.149****
	Switches	0.142	0.587
	Gender		**0.144****

†p<.10, *p<.05, p**<.01, p***<.001

6.3.3 Summary of Results

An overview of the results can be seen in Figure 6.7.

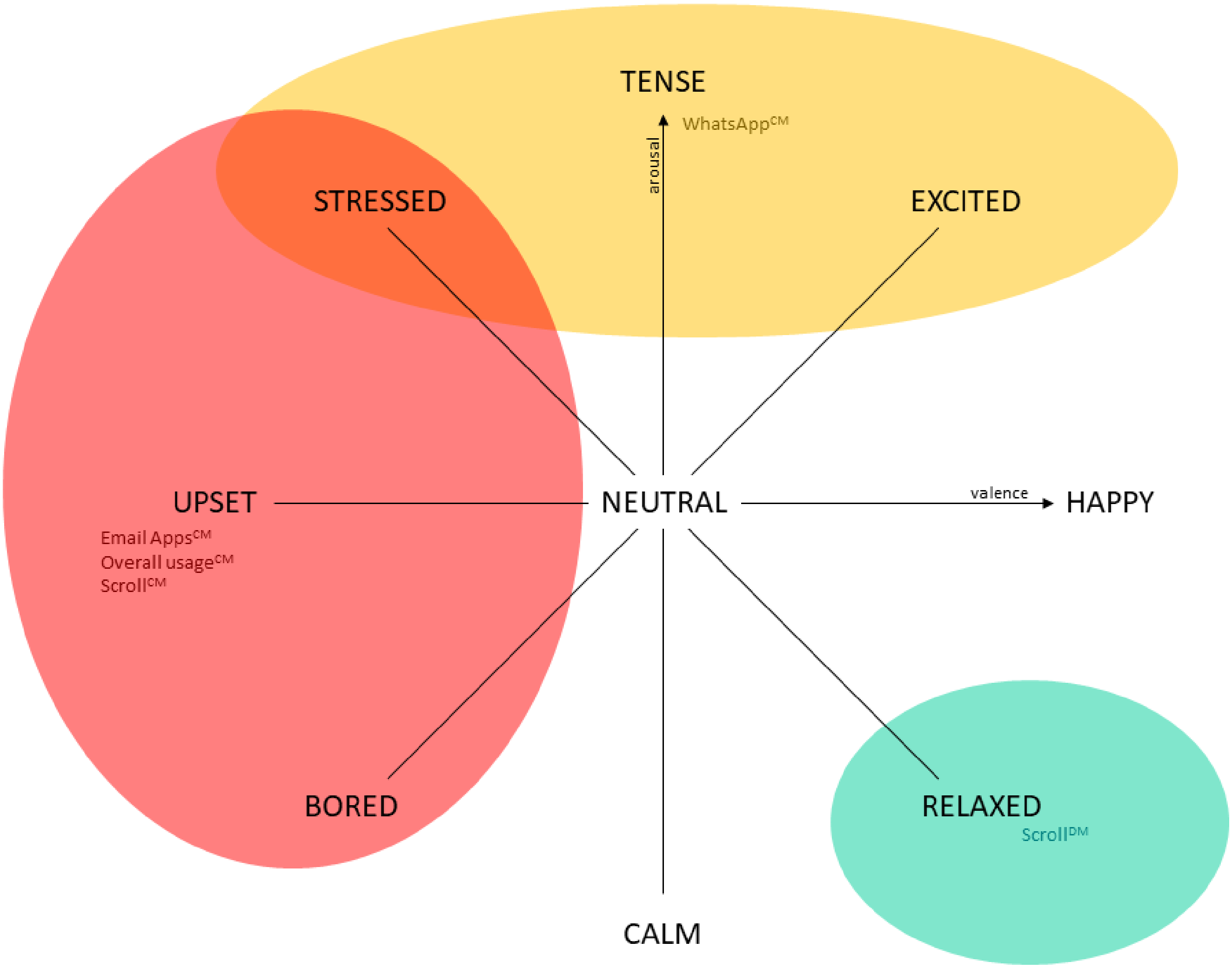


Figure 6.7: Results: Found associations for Study 1 (denoted by ^{CM}) and Study 2 (denoted by ^{DM}).

6.4 Discussion

Although finding associations between the low-level UI interactions and self-reported moods proved to be difficult in the examined time frames, a number of significant outcomes were uncovered.

We evaluated the predictability of mood based on a user's smartphone activity. Both CM and DM were assessed in reference to the previous hour and previous 12 hours of UI interactions respectively. Both approaches revealed to be complex: Though focused, the 1 hour time frame disregarded most of the collected data, leaving less popular apps and app categories to be analysed with little data, while the 12 hour time frame incorporated all data collected throughout the day with significant gaps between usage sessions, potentially obfuscating meaningful smartphone activity sessions in this way.

As expected, we found that the number of overall UI events in the hour preceding a CM report predicted the report of lower valence moods. This finding seems to provide support for Hypothesis *H1* and is consistent with numerous prior studies linking mobile use to negative moods (e.g., [39, 169, 7]). This result also points to heightened usage being potentially problematic and harmful and coincides with SA being associated with higher smartphone usage (see Chapter 4 and negative moods [83, 121, 54, 61]).

The usage of social media apps such as Snapchat and Instagram or any apps within the Social app category did not significantly contribute to the prediction of neither the valence nor the arousal of reported moods of CM or DM reports. Hypothesis *H3* was therefore not supported. This is an interesting finding considering the strong association uncovered in Chapter 4 between Social apps (and in particular Snapchat) and SA. Moreover, we find that overall Snapchat usage was partially predicted by daily reports of happiness and boredom in the preceding chapter, Chapter 5. From the results in this study however, it seems that Snapchat usage is not a consistent predictor of mood arousal nor mood valence.

Similarly, the use of communication apps did not predict the report of higher or lower valence moods either, providing no evidence for Hypothesis *H7*. Unexpectedly however, the use of the instant messaging app WhatsApp did predict the report of higher arousal CM reports. This finding could be explained by the higher urge to share experiences and therefore message friends or family when excited or stressed. Indeed, Berger [23] affirms that in comparison to negative, lower arousal moods such as boredom and being upset, negative high arousal moods such as stress and anger may increase the need to vent. Additionally, arousal seems to increase social transmission [22] and news articles eliciting high arousal moods are more likely to be shared with others [24]. Further investigation into this phenomenon in the context of mood prediction would be worth pursuing.

The usage of emails apps was identified as a predictor for negative valence CM moods, but had no association with mood arousal. This partially supports Hypothesis *H2*. Out of all results, the interaction between email apps and valence provided the steepest regression line slope, pointing towards a strong association. While previous literature [106] suggests a link between email app usage and stress, entailing a positive association with mood arousal, we did not replicate this in the present study.

The investigation of scroll events as a predictor of mood arousal and mood valence produced conflicting results, but providing some evidence for Hypothesis *H5*. While scrolling predicted more negative valence CM reports and lower arousal DM reports as expected, scroll interactions were found to be significant predictors of the report of more positive valence moods for DM reports as well. These results could partially be explained by the large proportion of scroll events encompassed in all UI interactions (see Section 2.3.3 and specifically Figure 2.5). As they are scattered in clusters throughout the day, the predictive impact of scrolling events might vary when looking at a 12 hour time frame. Additionally, the positive shift between CM and DM reports observed in our data in Chapter 3, and attributed to the Fading Affect Bias [202], could have impacted the prediction of CM and DM differently. Though not significant, we note a similar shift to a higher β coefficient for all studied UI interactions, except for usage of Facebook Messenger, Instagram, WhatsApp, and Music apps. In general, we observe a greater difficulty in predicting DM over CM, likely due to the greater spread of smartphone activity throughout the day and the previously noted lower accuracy for DM reports (see Chapter 3). This points towards the greater fit of CM reports when studying user behaviour at a fine-grained level.

Lastly, we note that in comparison to women, men reported significantly lower arousal moods. Although gender was investigated as a confounding variable in the analyses conducted in Chapter 3, no difference was found then when looking at each separate mood. Looking at these moods translated to valence and arousal coordinates according to the Circumplex Model of Affect [164] (see Figure 6.2 and Table 6.1) however, an effect for gender was identified. This is consistent with findings by Coren [46] who found women to have a higher mean arousability as measured on the Arousal Predisposition Scale and highlights again the importance of checking for confounding factors in studies relating to human behaviour and affect.

Overall, evidence for the support of Hypothesis *H1* and partial support of Hypotheses *H2* and *H5* was discovered. However, no support was found for Hypotheses *H3*, *H4*, and *H6-9*. We note that for the uncovered significant results, only small effect sizes were found, potentially pointing towards the need for a larger sample size and an adjustment in sampling time frame. These results however are quite significant in their own right. Although not all hypotheses were supported, a link between specific UI interactions and mood was found for some cases, indicating that UI interactions can successfully be used as a proxy to quantify user behaviour. It is conceivable that given a greater sample size, more associations could be uncovered. Furthermore, while CM reports seem to be a better fit for the analyses in this chapter, an evaluation looking into different time window choices for the count of UI interactions might provide useful to assess what amount of time is needed to capture meaningful user behaviour.

6.5 Conclusion

In this chapter, we have investigated the predictive capacity of specific UI interactions for both CM and DM reports. Most importantly, we note more negative current moods being reported followed by higher overall usage, email apps and increased scrolling activity. This further strengthens claims pointing towards heightened smartphone usage, which is in turn associated with SA (see Chapter 4), having negative effects on user mood. Work related activities such as managing one's emails in particular seem to contribute to more negative mood reports. These findings may inform design choices in interventions targeted at mood improvement and heightening user well-being.

We also note differences in findings characterising activities predicting CM and DM reports. This further seems to point towards current moods' higher accuracy enabling the better discerning of small effects in user behaviour and indicates favouring higher frequency ESM sampling would be beneficial when observing micro-behaviours.

Furthermore, we observe again the adequacy of using UI interaction events as proxy for smartphone usage behaviours. Although the number of such events was severely restricted by the time frames investigated in this chapter, meaningful results could be derived from some of the analyses performed.

Overall, this chapter has made the following contribution (see Section 1.5) to this thesis:

C5 Analysis of mood predictors: identification of app interaction behaviours preceding mood states and further evidence for the value of UI interaction events as proxy for smartphone usage behaviours.

Chapter 7

Discussion and Conclusion

The overall exploratory research effort presented in this thesis has led to new insights in the fields of ESM methodology, SA, smartphone usage and smartphone based mood prediction. In this chapter, we will highlight the contributions made and the new knowledge brought forward in this work. We summarise the results obtained through Chapters 3-6 in Section 7.1. We further discuss in more depth our novel approach to the measurement of smartphone usage (Section 7.2.1), implications of current trends in smartphone and app usage (Section 7.2.2) and the generalisability of the results reported in this thesis (Section 7.2.4).

7.1 Summary of Results

7.1.1 Timing in ESM (Chapter 3)

In Chapter 3, we assessed the impact of using two different sampling frequencies for mood in an ESM study. This was done by looking at the matches of current and daily moods. We find a significant overlap between the two reporting frequencies, pointing towards the interchangeability of both methods. Our data also indicates that none of the intrinsic human characteristics (e.g., age, personality) that we have investigated have a mediating effect between matches of current and daily moods. This finding indicates that sampling frequency does not need to be adjusted for a specific participant population if it is characterised by any of the examined characteristics. While this finding was also true for gender, we found in Chapter 6 that men reported significantly lower arousal daily moods than women, but did not uncover a similar pattern for current moods. The gender differences for arousability predisposition have been noted in literature before [46]. Reevaluating this in the context of different higher sampling frequencies may be of interest in future research.

However, we do find differences that should be taken into account when designing an ESM study. Particularly, we note that a higher completion rate is found for daily rather than current mood reports. The higher number of micro-survey prompts and thus potential disruptions may have primarily contributed to the relative higher number of CM survey dismissals. This indicates that a lower frequency of mood reports may be favoured if participant compliance is essential to the study. On the other hand, a lower, 1 per day frequency for mood reports might lower the accuracy of the recorded mood if a summary for the day is requested. When comparing DM reports to CM for the same day, we found that certain current moods were more likely to match that day's reported daily mood. Specifically, the last but also the first reported CM, the CM report with the highest intensity and with the most positive mood were more likely to coincide with the same day's DM report. These findings indicate that memory biases (specifically the serial position effect [141], the Peak-end rule [73], and the Fading Affect Bias [202]) have an impact on the choice of DM mood for participants. This suggests that DM reports might be not reliable enough for certain analyses. Our results in Chapter 6 partially demonstrate this as few associations between a user's daily smartphone usage and daily mood were found in comparison to the same analysis focusing on shorter 1 hour time frames and current mood.

7.1.2 User Interaction: Smartphone Addiction and Snapchat (Chapters 4 and 5)

In Chapter 4, we sought to identify smartphone user behaviours that contribute to SA. In this exploratory study, we focused specifically on active usage measured by physical interactions with the phone and examined SA's link to overall usage and the 5 smartphone usage behaviours that could be unambiguously attributed to "active" usage (tap, long tap, writing, scroll, and text selection). We further looked into the activity of users in the 29 and 21 most popular apps and app categories more specifically. Results indicated that usage of Social and Lifestyle apps in particular were associated with higher scores on the SAS scale, indicating a higher proneness to SA. While the former result adds to the existing literature linking social media usage to SA (e.g., [65, 95] and FoMO (e.g., [8, 157]), the latter result has not been reported previously to the best of our knowledge. Being a very diverse app category, with apps varying between blogging, slimming, store reward or brand, fortune-telling or period tracking apps, it is difficult to ascertain what characteristics make it more used by individuals scoring higher on the SAS scale. We believe that it may be the higher interaction with these apps that may be regarded as more personalised that may contribute to its link with SA. While all evaluated social media apps showed a positive association with SA to some extent (see Table 4.2), results for Snapchat and especially for female users were particularly strong.

These results led us to specifically examine this recently become popular app in Chapter 5 and investigate which user characteristics and behaviours were especially predictive of Snapchat usage. Both survey and smartphone interaction behaviours were taken into account. Unsurprisingly, we found SA score to be an important predictor alongside age, sleep amount, wake up frequency, daily happiness and boredom, Conscientiousness score, and interactions with a few different apps.

7.1.3 User Interaction and Mood (Chapter 6)

In Chapter 6, we examined smartphone interactions preceding mood reports on both a smaller 1-hour and a larger 12-hours timescale to determine whether specific usage behaviours could predict specific moods. To achieve this, we converted the categorical mood data from the CM and DM reports to continuous 2 dimensional data following their position on the Circumplex Model of Affect [164]. Additionally, intensity measures were included for CM reports.

Our results reveal a few interesting associations. Firstly, we observed higher overall smartphone usage preceding more negative current mood reports. This finding is in line with previous research attributing negative effects on health and well-being to excessive screen-time and SA [169, 7, 61].

Secondly, a similar association was found for the use of email applications and heightened scrolling activity, again for CM reports. While we predicted the negative association with mood valence for both of these usage activities, no evidence for the predictability of mood arousal was found. We also note that the examination of DM reports resulted in only one significant finding, the association of scrolling events with more positive and lower arousal moods, that stands in conflict with the preceding finding for CM reports. This finding is interesting in the light of the positive shift (attributed to the Fading Affect Bias [202]) in reports we see between current and daily moods uncovered in Chapter 3. Similarly, we would also like to point out the greater number of negative associations with valence with no positive associations being found for CM reports. Current moods therefore seemed to be most influenced negatively by smartphone usage, but usage might be remembered as having a more positive impact on user mood on a greater daily time-scale.

7.2 Discussion and Future Work

7.2.1 Quantifying smartphone use

In this thesis, we have chosen to measure smartphone usage by counting the number of interaction events occurring whenever the user is active on their phone. To the best of our knowledge, this is the first study working at this granular level and constitutes a new form of human-smartphone interaction analysis. And in contrast to studies using session duration [67, 87], this method allows for the additional capture of intensity of usage and excludes passive usage which might occur when the smartphone screen is switched on even though the user is not necessarily interacting with their phone. Not all smartphone events can be used in this approach however and making a distinction between human-generated and potentially smartphone-generated events is necessary in order to truly only focus on user activity. This requires the exclusion of any events that could also be generated by the smartphone itself (e.g. an app opens another app that generates an "window state changed" event). This resulted in the sole consideration of 5 type of interactions: tap, long tap, scroll, text selection, writing.

The advantage of this methodological choice was demonstrated in Chapter 4 focusing on the capturing usage behaviours linked to SA. As depicted in Figures 4.1 and 4.2 and described in the results of that chapter, the number of UI interaction events was a better indicator of SA than the duration of smartphone usage. Measuring UI interaction events thus allowed for a more robust and less noisy quantification of user activity. The focus on active usage allowing for a clearer signal representative of human behaviour was also shown in Chapter 6, where mood valence and arousal could be predicted based on specific UI interactions, reaffirming the value of using human-smartphone interaction events as proxy for the quantification of smartphone usage behaviours.

While we only considered two options for the measurement of smartphone usage (UI interactions vs. session duration), a third, hybrid option could be considered in future work as well. By bundling events that are close in time together, the data could be aggregated in a meaningful way by adding a temporal component. This could be particularly interesting for the consideration of inter-individual differences in smartphone use (e.g. typing speed [66]).

Furthermore, UI interaction data as collected for this project lends itself well to feature extraction, which could reveal more meaningful relations that may have been overlooked due to the complexity of the data. Pattern recognition in particular may be relevant in revealing additional smartphone usage habits hidden in specific interaction event sequences that may be relevant in studying micro-habits. Significant work has already been led by Turner and colleagues [194] and is worthy of further pursuit.

7.2.2 Trends in Smartphone Usage

In Chapter 1, we discussed how recent of a phenomenon the smartphone is and how quickly the mobile phone industry has changed in the recent years. On a smaller time frame and within the smartphone era however, it is also of importance to note trends and changes in the usage of apps too.

In the Social app category for example, Facebook is to this day still the most popular app on the platform and the only Social app having achieved more than 5 billion downloads [12]. Facebook's popularity is however decreasing with the younger generations, that have switched to newer platforms such as Instagram, Snapchat and more recently, TikTok [160]. In comparison to the now more established Snapchat, especially popular among Millenials, TikTok has been described as the app primarily used by Gen Z [152] revealing preferences of different social media applications per user generations. This is unsurprising considering the faster adoption rate of new social media and new technology by younger people [115]. These generational particularities therefore have important implications for research conducted on social media and more generally smartphone usage.

Towards future work, studying the impact, in particular with respect to SA and FoMO, of newly popular apps would be of interest to draw parallels between similar apps used by different user groups in different times. This could bring a new perspective to the discussion of the smartphone being either the source or the pathway to addiction.

It is also worth noting that smartphones, while being the most popular and ubiquitous, are not the only "smart" device in use today. Smartphones communicate with an increasing number of other smart products within the Internet of Things (IoT). Smart watches and smart TVs, for example, have been growing in ubiquity in UK households [183, 184]. Within the wider topic of Internet Addiction, the interaction of smartphones -and SA- with other IoT devices would be of interest to investigate. Analysing usage patterns across devices by tracking UI interactions could be particularly meaningful to examine in the context of a daily routine where users may switch from device to device in similar a fashion every day.

7.2.3 Potential of a Wider Dataset

While a broad range of data was collected and analysed for this thesis (see Chapter 2), there is room for obtaining additional context data that would be of interest to examine in parallel or in combination with the methods used here.

Firstly, location data acquired either through collecting the smartphone's GPS data and/or requesting participants to report their presence in particular locations, e.g., home, work, social environment, etc. This type of data, not uncommonly collected in ESM studies [27, 111], could give us a deeper understanding as to why certain moods and behaviours could occur. For instance, the duration and frequency of commutes could have different impacts on smartphone usage, be tied to more or less usage habits and different usage patterns. The context, the smartphone usage, and user mood may all influence each other. Having access to location data therefore would provide interesting complimentary information to consider.

Secondly, we note that collecting textual data (i.e., from text messages, social media posts) would give us the opportunity to perform sentiment analysis that would provide an interesting frame of reference in particular within the context of the studies conducted in Chapters 5 and 6. Does the sentiment of messages sent on Snapchat influence overall Snapchat usage? Does the sentiment extracted from certain apps overlap more with the reported mood than others?

Lastly, and especially in the context of the work done in Chapter 6, additional haptics data would be of interest to consider. In particular, typing/handling speed, pressure exercised on the phone, or the size of phone-hand contact area would be interesting variables to consider when predicting user mood. Typing speed for example may contribute to the detection of arousal while pressure may be an indicator of mood intensity.

7.2.4 Generalisability of Results

In this thesis, we used data collected from a subset of 64 participants, who due to the recruitment method and recruitment criteria had considerable overlap in individual characteristics. This has consequences for the generalisability of our results.

Firstly, all recruited participants were Android users as using a smartphone running Android 4.4 or higher was one of the prerequisites to be able to install and use our app *Tymer*. While Android has the greatest market share for smartphone operating systems in the world (85% followed by iOS at 14% [180]), it should be noted that differences exist in personality, gender and age between Android and iOS users. Shaw and colleagues [171] have notably reported that iOS users were more likely to be female, younger and score higher on the Emotionality facet of the HEXACO personality scale in comparison to Android users, who scored higher on the Honesty-Humility and Openness to Experience facets of the same personality model, but also displayed higher levels of Avoidance Similarity. This could have impacted our results specific to SA in Chapter 4 as Emotionality has been positively correlated to problematic smartphone use while a negative association was found with individuals scoring higher on both

Honesty-Humility and Openness to Experience [90].

Secondly, most recruited participants (80%) were students and more than half of them had obtained a Bachelor's degree or higher (66%), this is significantly higher than the national average (43% [72]). Age was also skewed positively ($M = 25.4, SD = 5.87$). Many academic studies use student participants, a practice which has been criticised for its problematic generalisability to the general public. Student samples were found to vary randomly from the general public for various variables pertaining to personality and attitudes, making it difficult to assess how findings could be generalised for a wider population [84]. In the context our work, the median age of our participants could have contributed to the discovery of interactions with the Snapchat app in particular as this app was especially popular in this age group [179]. More generally, it is difficult to estimate how our participant sample specifically varies from national and international averages. Replication with a bigger and more varied population would therefore be of use.

Thirdly, we note that our sample population is based in the UK, which due to cultural and socio-economic differences may not be representative of the global population. In the context of the study of smartphone user experience, cultural differences have been identified in the way users interact with their phone [123], but also their attitudes towards it [204]. For the UK particularly, previous research has found that users are more likely to download a new app out of impulse, be influenced by the app price, and not rate the app they downloaded. In the context of this thesis, it is also interesting to note that UK app users were more likely to download Lifestyle apps than app users from Russia, Japan and France [123]. This might partially explain why we were able to uncover an association between this app category and SA that we have not previously seen reported in the literature.

Lastly, we note that with a relatively small sample size of 64 participants, generalisations should always been made with caution and we would like to again stress the value of replicating the studies discussed in this thesis with a greater and more varied population. This would not only allow for a more reliable generalisation of the results but also for a greater effect size in the analyses.

7.3 Final Conclusion

In this thesis, we have introduced a new methodological alternative for the quantification of human behaviour on smartphones. The use of UI interaction events as proxy for smartphone usage provides significant advantages over commonly used approaches such as using cumulative session duration times or self-report methods. Through this, we make a contribution to the ESM methodology by highlighting the value of low-level UI interactions as a useful source of complementary data.

Furthermore, we have presented evidence for associations between specific usage behaviours and Smartphone Addiction, but also the experience of different moods, strengthening findings reported in previous literature and bringing forward new knowledge in these topics. We could thus bring forward new understanding of human-smartphone interactions and the substitutive role of the device in revealing an individual's disposition. Smartphones not only help to extend human cognition, but also provide a window into human's cognition.

Appendix A

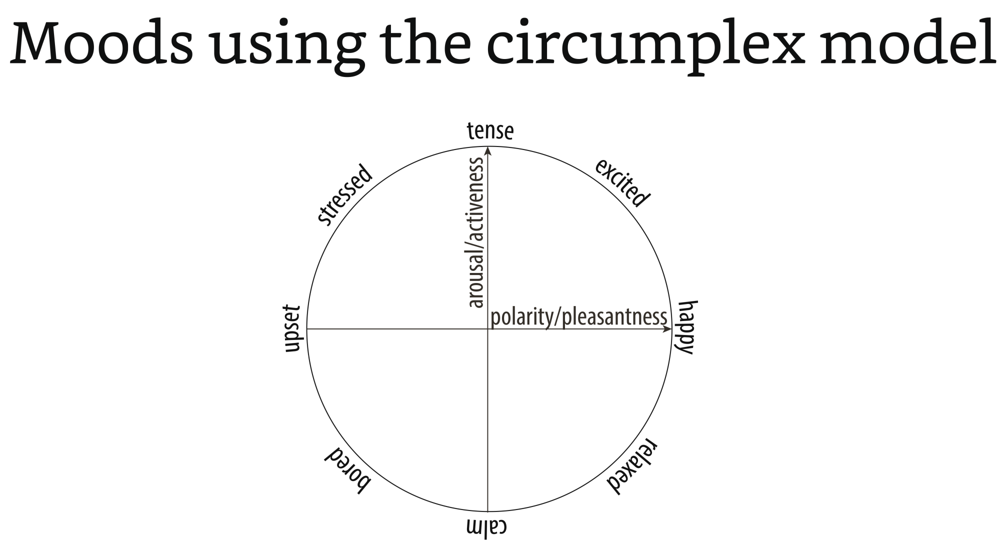
Complimentary text, graphs and tables to the thesis

A.1 Chapter 2

A.1.1 Briefing Session Presentation

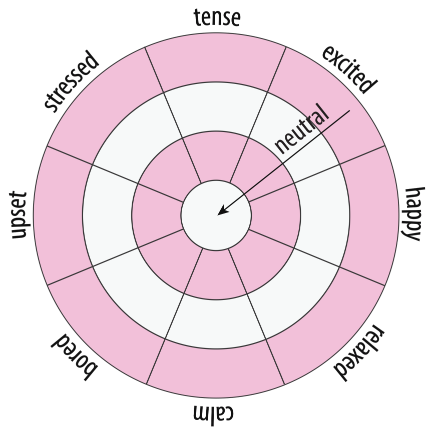
The following slides were included in the presentation given during the Briefing session to explain differences between moods and intensities.

Slide 1



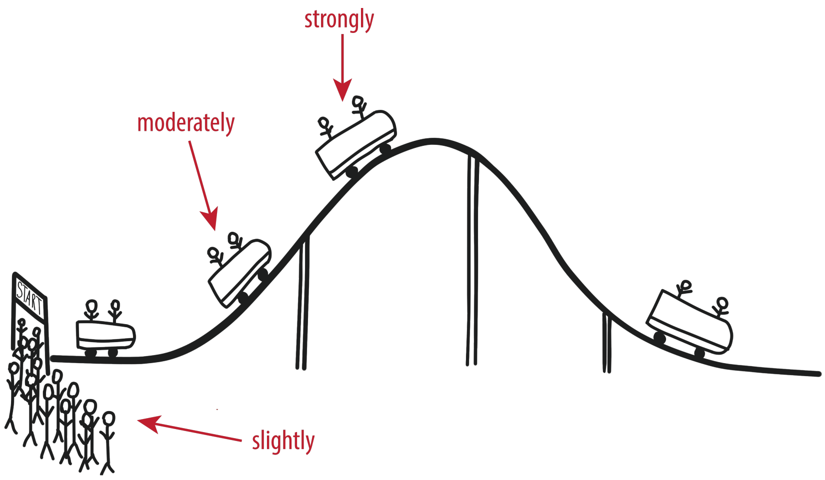
Slide 2

Moods using the circumplex model

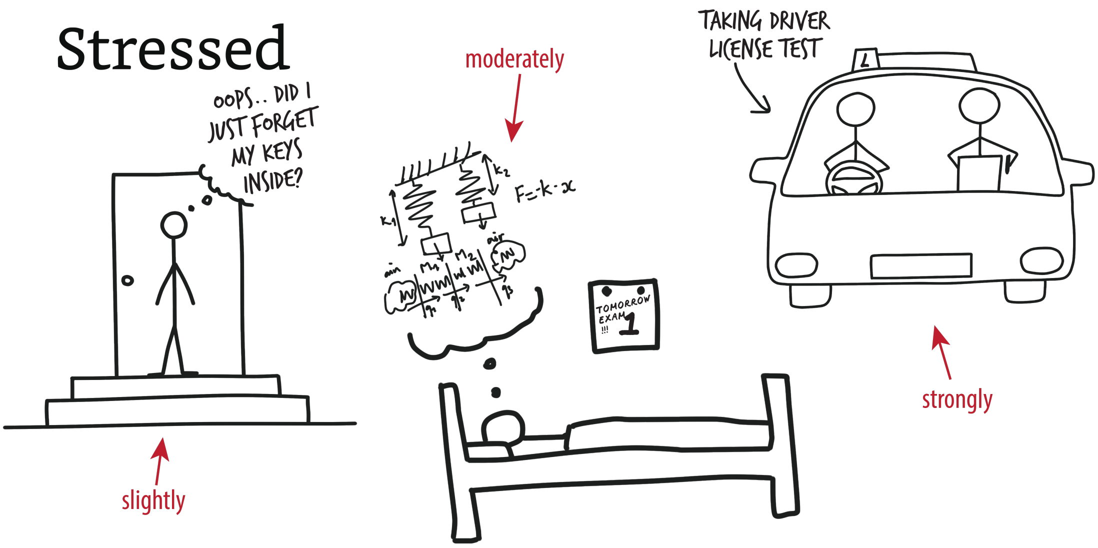


Slide 3

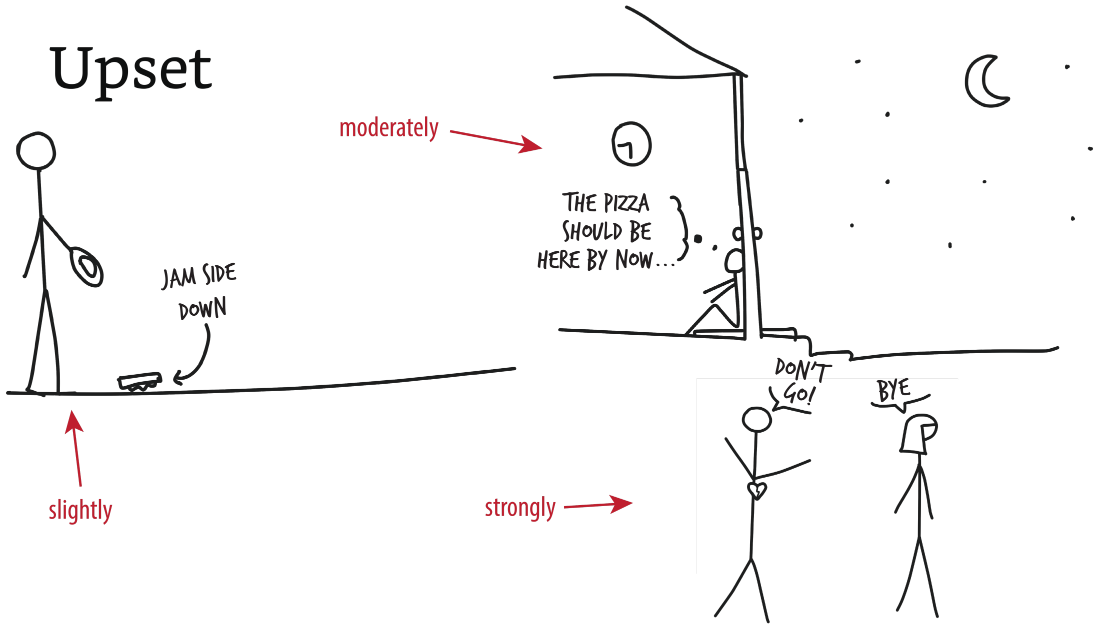
Tense



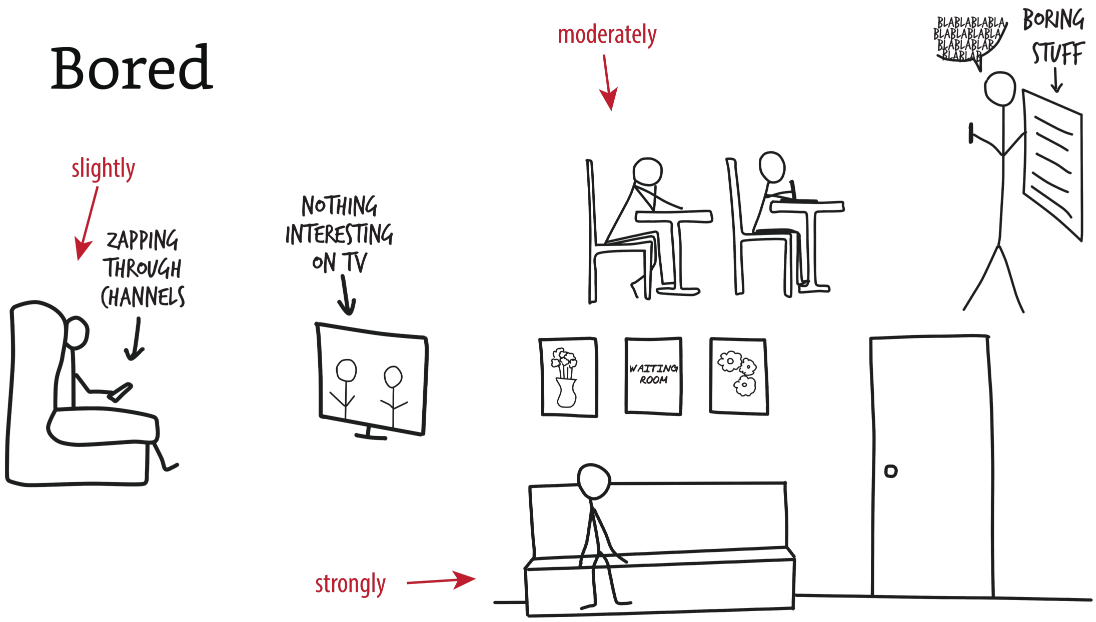
Slide 4



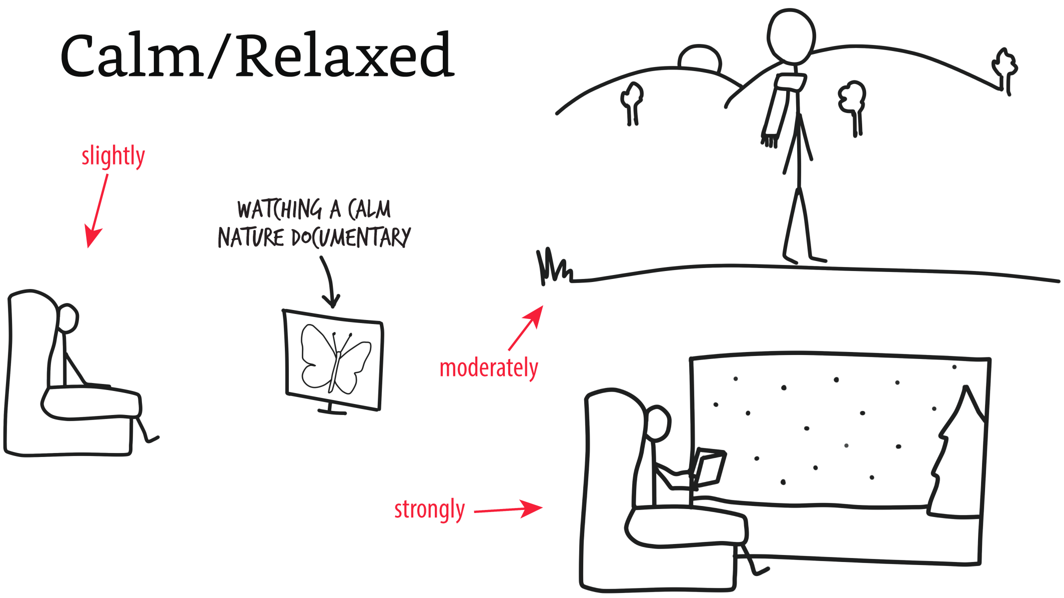
Slide 5



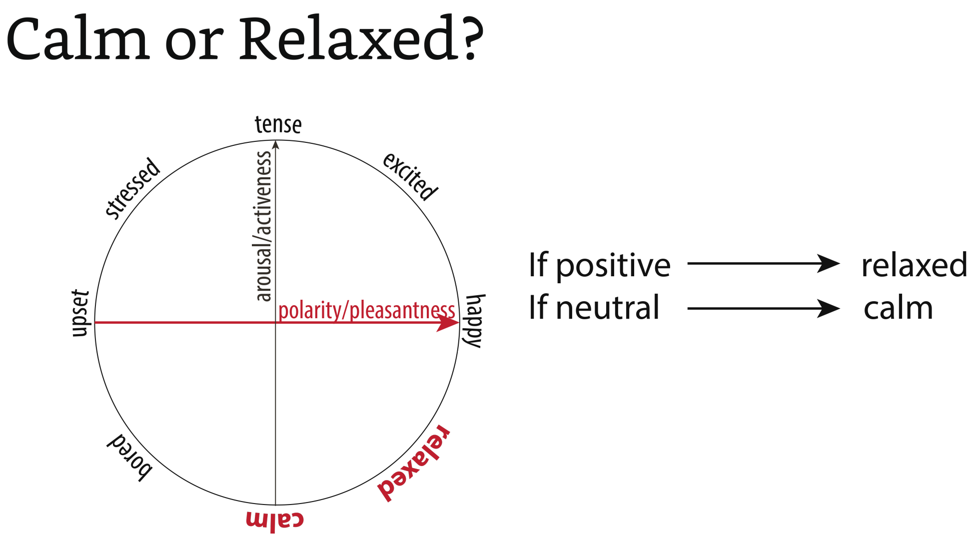
Slide 6



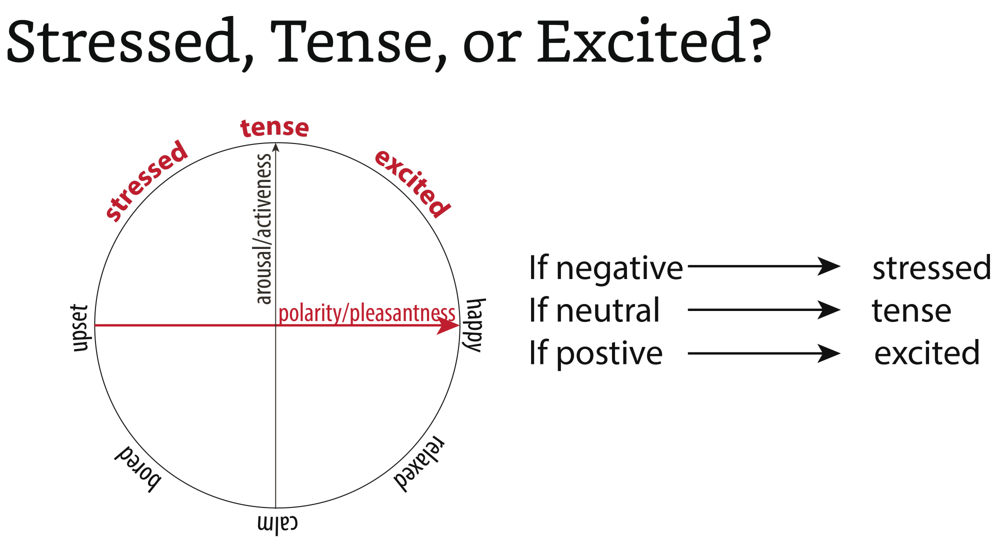
Slide 7



Slide 8

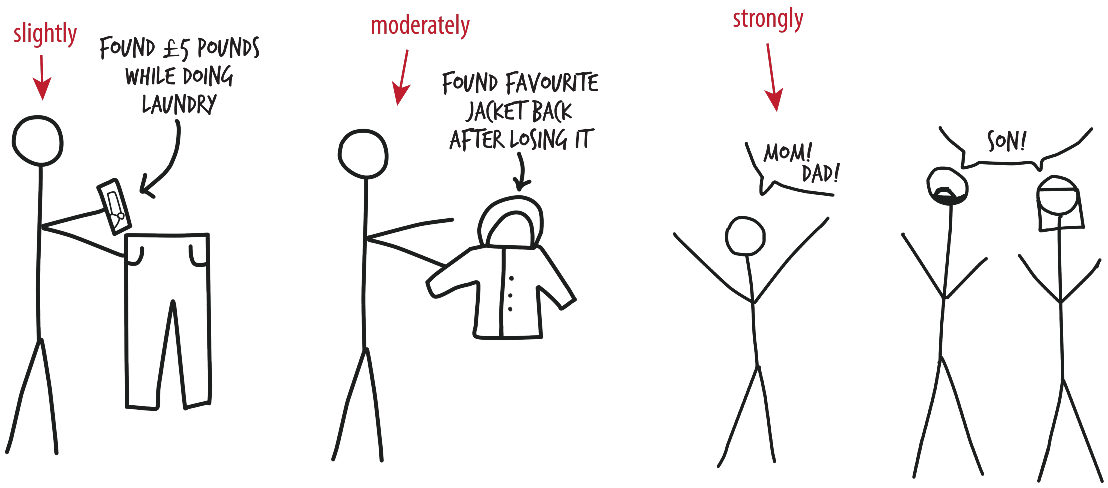


Slide 9



Slide 10

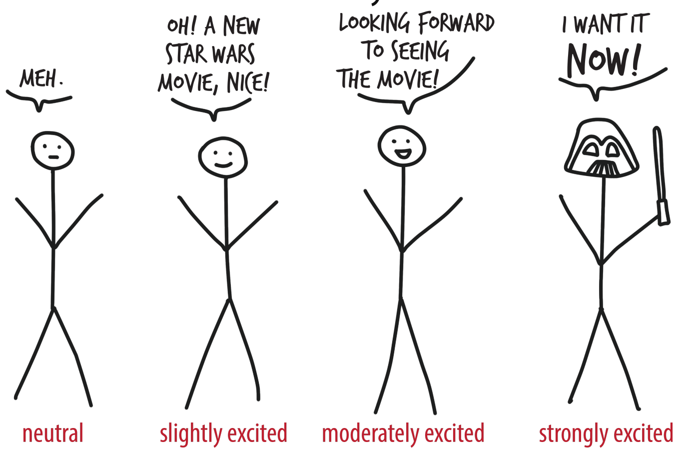
Happy



Slide 11

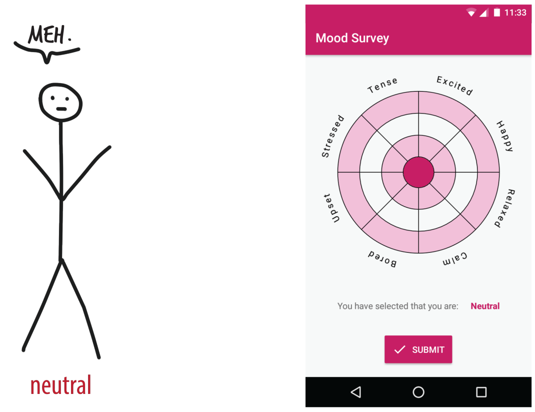
Excited

Try to remember how you felt when you heard a new Star Wars movie would come out. How excited were you?



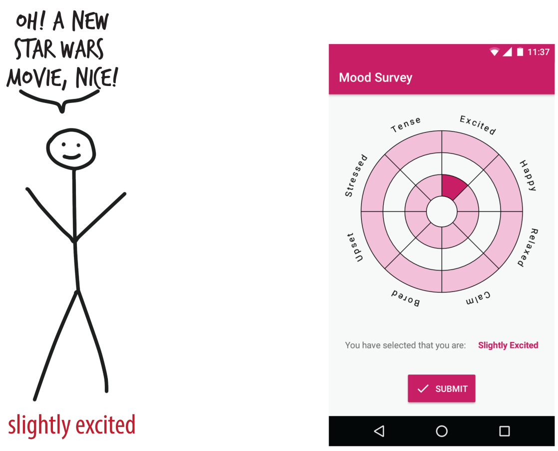
Slide 12

Reporting the mood in the app



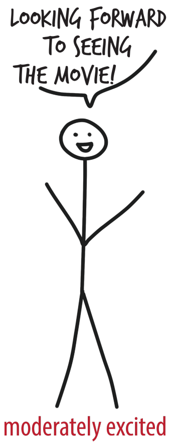
Slide 13

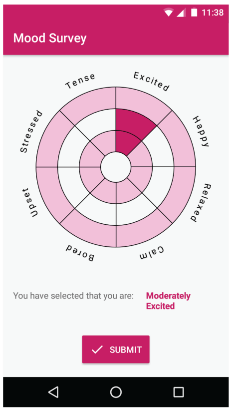
Reporting the mood in the app



Slide 14

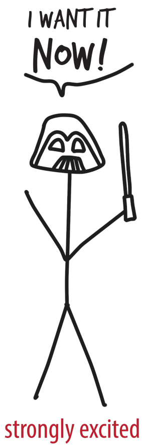
Reporting the mood in the app

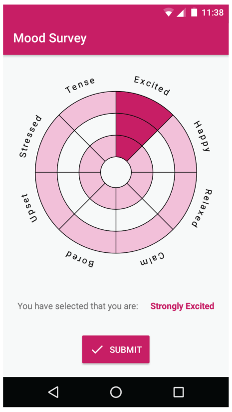




Slide 15

Reporting the mood in the app





A.1.2 Demographics and Smartphone Usage Questionnaire (DSUQ)

Background Details:

1. Age
2. Sex
3. Height
4. Weight
5. Handedness:
   - ○ Right
   - ○ Left
6. Bilingual:
   - ○ Yes
   - ○ No
7. Native English speaker:
   - ○ Yes
   - ○ No
8. First language
9. How would you describe your race?

Life:

10. Employment status:
    - □ Employed full-time

- ☐ Student
- ☐ Employed for wages
- ☐ Homemaker
- ☐ Retired
- ☐ Employed part-time
- ☐ Out of work and looking for work
- ☐ Out of work but not currently looking for work
- ☐ Military
- ☐ Unable to work

11. If employed or working, when do you work?
    - ○ During the day
    - ○ During the night
    - ○ Shifts at various hours
    - ○ Other
12. If not currently employed, how long ago since you last worked?
13. If you stopped working before retirement ages, please give reason
14. What is the highest degree or level of school you have completed?
    - ○ No schooling completed
    - ○ Primary school
    - ○ High school, no diploma
    - ○ High school diploma or the equivalent
    - ○ Some undergraduate education, no degree
    - ○ Trade / technical / vocational training

- ○ Associate degree
- ○ Bachelor's degree
- ○ Master's degree
- ○ Doctorate degree

15. Do you live:
    - ○ Alone
    - ○ With partner
    - ○ With friends
    - ○ Other

16. Income:
    - ○ For my age group, I consider my income to be below the average income
    - ○ For my age group, I consider my income to be an average income
    - ○ For my age group, I consider my income to be above the average income

Smartphone Use:

17. I usually use my smartphone with:
    - ○ Two hands
    - ○ My left hand
    - ○ My right hand

18. When I sleep, my smartphone is:
    - □ In another room as me
    - □ In the same room as me, near the bed
    - □ In the same room as me, not near the bed

- □ Switched off
- □ Switched on, on loud mode
- □ Switched on, on alarms only
- □ Switched on, on silent mode

19. When I sleep, notifications, messages or calls from my smartphone:
    - ○ Wake me up at least once per night
    - ○ Sometimes wake me up
    - ○ Never wake me up
20. I consider my smartphone usage amount to be
    - ○ Below average
    - ○ Average
    - ○ Above average
21. What apps or in-built smartphone features do you use most? Please give a ranking stating the app or feature name and their position (1. for the most used app or feature)
22. What apps or in-built smartphone features are most important to you? Please give a ranking stating the app or feature name and their position (1. for the most important app or feature)

A.2 Chapter 5

A.2.1 Regression models

Snapchat usage and survey data

Predictors were entered in the following blocks:

1. Block 1 (confounding factors): Age, Gender
2. Block 2: Smartphone Addiction, Happy, Bored
3. Block 3: Tense, Agreeableness, Impulsivity, Sleep amount
4. Block 4: Calm, Upset, Extraversion, Openness to Experience,
5. Block 5: Conscientiousness, Excited, Stressed, Wake Up
6. Block 6: Sleep quality, Neuroticism, Neutral, Relaxed

Snapchat usage and smartphone interaction data

Predictors were entered in the following blocks:

1. Block 1: WhatsApp, Facebook Messenger
2. Block 2: Instagram, BBC News
3. Block 3: Messaging, Google Quick Search Box, YouTube
4. Block 4: Google Calendar, Amazon Shopping, Phone, Google Play Store, Twitter
5. Block 5: Google Maps, Google Keep, Amazon Shop UK, Outlook, Skype
6. Block 6: Google Hangouts, WeChat, Settings, Chrome, Facebook
7. Block 7: Google Photos, Calculator, Gmail, Spotify, Tinder, Contacts

Snapchat usage and survey and smartphone interaction data

Predictors were entered in the following blocks:

1. Block 1 (confounding factors): Age, Gender

2. Block 2: WhatsApp, BBC News, Smartphone Addiction
3. Block 3: Gmail, Wake Up, Sleep amount, Amazon Shop UK
4. Block 4: Happy, Conscientiousness, Facebook Messenger
5. Block 5: Agreeableness, Neuroticism, Google Quick Search Box, Spotify, Outlook
6. Block 6: Tense, Calm, Openness to experience, Google Calendar, Chrome
7. Block 7: Facebook, Youtube, Calculator, Google Play Store, Phone
8. Block 8: Tinder, Google Hangouts, Instagram, Impulsivity, Google Photos, Contacts
9. Block 9: Settings, WeChat, Skype, Messaging, Excited, Extroversion
10. Block 10: Google Maps, Twitter, Amazon Shopping, Stressed, Upset, Neutral

A.3 Chapter 6

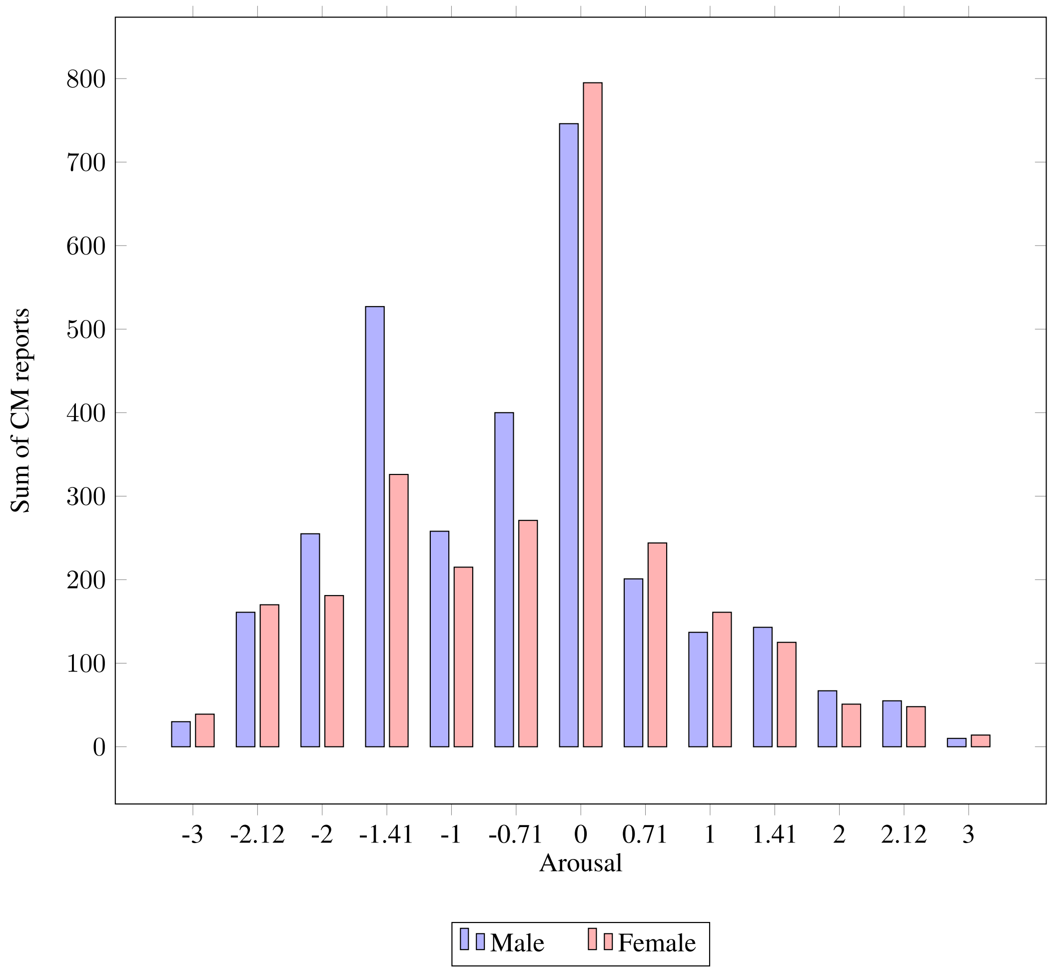


Figure A.1: Sum of CM reports per arousal level per gender.

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