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Nudging problematic smartphone use to a lower level

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2016 Laurea

Laurea University of Applied Sciences

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Palokangas, Lauri
Behavioural insights in business applications
Master's Thesis
November, 2016

Laurea University of Applied Sciences **Abstract**
Degree Programme in Behavioural Insights in Business Applications
Master's Thesis

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Nudging problematic smartphone use to a lower level

Year 2016 Pages 100

Smartphone usage has evolved in people's lives from a necessity to a habit, in some cases leading to compulsive use and addiction. Extremely frequent smartphone usage and usage in excess durations has previously been classified using criteria known from other addiction research. However, little research has been performed to understand Problematic Smartphone Use (PSU) on healthy test subjects. In the same way, there are only few studies that have focused on the prevention of PSU. Behavioural economics, and nudges defined by Thaler and Sunstein provide frameworks that can be applied to investigate how smartphone users respond to nudges that try to lower their smartphone usage. The information can be used to find ways to lower the susceptibility to problematic smartphone use, and the resulting consequences.

The research included four research questions. The first question asked how the results of self-assessment are associated with the characteristics of smartphone use amongst healthy users. The second question asked how nudges influenced smartphone usage. The third question asked how nudges that were designed to improve Capability, Motivation or the effect of Goal-attainment lowered the smartphone use. Finally, the fourth research question asked whether smartphone usage relapsed to previous behaviours once the nudges were no longer present. 170 test subjects took part in the research by responding to the smartphone addiction self-assessment. 77 of the test subjects completed a five-week research that investigated the effect of nudges on smartphone usage key indicators. Research data was collected with a psych app developed for the purpose, and analysed using the Hilbert-Huang method in Matlab and with inferential statistics in SPSS.

According to the results, there were statistically significant differences in the key indicators of smartphone usage between groups that were formed based on a score derived from the smartphone addiction self-assessment. Test subjects with a higher score unlocked their smartphone more often and more frequently. However, as the score of the self-assessment does not predict key indicator levels of smartphone use, the score cannot be used in itself to identify individuals susceptible to problematic smartphone use.

A statistically significant effect was found in the interaction between Group and Stage for total phone usage time when the effect was compared between baseline and the nudges. The results suggest that the effect of the Capability-nudge was significant enough to lower the total duration of daily smartphone usage. According to the results, the type of nudge does not explain the magnitude of change in smartphone behaviour. The results suggest that using nudges that increase Capability or Motivational components can result in influential behaviour change. However, based on evidence collected from this research, there was no significant change in any of the key indicators between different types of nudges.

Relapse in smartphone usage was observed after the nudges were no longer in effect. Intermittent glancing, as well as the median session time increased during the observation period. It can be suggested that there are statistically significant differences in how individuals respond to nudges. For those with a high score in smartphone addiction self-assessment, nudges may help lower daily total smartphone usage time.

Keywords: addiction, behavioural insights, nudge, psychoinformatics, smartphone

Laurea-ammattikorkeakoulu **Tiivistelmä**
Päätöksenteon ilmiöt johtamisessa, kehittämisessä ja asiakastyössä
Tradenomi (Ylempi AMK)

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Älypuhelimen ongelmallisen käytön alentaminen tuuppaamalla

Vuosi 2016 Sivumäärä 100

Älypuhelimen käyttö on ajan mittaan muuttunut tarpeellisesta käytöstä tavaksi; toisille tämä on johtanut pakkomielteiseen käyttöön ja riippuvuuteen. Äärimmäisen tiheästi toistuvaa tai pitkäkestoista älypuhelimen käyttöä on luokiteltu samoilla kriteereillä, kuin muitakin riippuvuuksia. On kuitenkin vähän tutkimuksia, jotka keskittyvät älypuhelimen ongelmalliseen käyttöön (Problematic Smartphone Usage) terveillä koehenkilöillä. Yhtä lailla on saatavilla vain harvoja tutkimuksia, jotka keskittyvät älypuhelimen ongelmallisen käytön ehkäisemiseen. Tässä tutkimuksessa käytetään käyttäytymistaloustiedettä ja tuuppausta interventiotutkimuksena, jotta ymmärretään, miten älypuhelinten käyttäjät reagoivat älypuhelimen käytön alentamisyrityksiin. Tietoja voidaan käyttää keinoihin alentaa alttiutta älypuhelimen ongelmalliseen käyttöön ja siitä johtuviin seurauksiin.

Empiirisessä osassa etsittiin vastauksia neljään tutkimuskysymykseen. Kyselyn avulla selvitettiin, miten riippuvuus älypuhelimesta on yhteydessä älypuhelimen käytön tunnuslukuihin. Toinen tutkimuskysymys oli, miten tuuppaukset vaikuttivat älypuhelimen käyttöön. Kolmantena selvitettiin, miten tuuppaukset, jotka paransivat osallistujien kykyä, motivaatiota tai tavoitteen saavuttamista, alensivat älypuhelimen käyttöä. Lisäksi selvitettiin, mille tasolle älypuhelimen käyttö palautui tuuppausten jälkeen. 170 koehenkilöä osallistui tutkimukseen vastaamalla älypuhelinriippuvuutta mittaavaan itsearviointiin. Näistä 77 koehenkilöä suoritti viiden viikon mittaisen tutkimusjakson, jossa selvitettiin tuuppausten vaikutusta älypuhelimen käyttöä mittaaviin tunnuslukuihin. Tutkimusaineisto kerättiin tarkoitukseen kehitetyllä psykoinformatiikan sovelluksella, ja analysoitiin Matlab-sovelluksessa Hilbert-Huang metodin avulla. Tilastolliset päättelyt tehtiin SPSS-sovelluksessa.

Tulosten mukaan itsearvioinnin vertailuluvun pohjalta muodostettujen Low- ja High-ryhmien välillä oli tilastollisesti merkitsevä ero, kun käyttöä arvioitiin älypuhelimen käyttöä mittaavilla tunnusluvuilla. Itsearvioinnissa korkean vertailuluvun saaneet käyttäjät avasivat älypuhelinta lukumääräisesti useammin päivän aikana ja käyttötapahtumien välinen mediaaniaika oli lyhyempi. Koska tutkimuksessa saatu itsearvioinnin vertailuluku ei ennusta puhelimen käytön tunnuslukuja, ei itsearvioinnin vertailulukua voi sellaisenaan käyttää älypuhelimen ongelmallisen käytön tunnistamiseen.

Kontrollijakson ja interventiojaksojen välillä oli tilastollisesti merkitsevä vaikutus, kun puhelimen päivittäistä kokonaisaikaa verrattiin ryhmien välillä. Tulosten mukaan tuuppauksen vaikutus oli riittävän voimakas alentamaan älypuhelimen käytön päivittäistä kokonaiskäyttöaikaa. Tulosten perusteella ei ole kuitenkaan mahdollista päätellä, että tuuppauksen muoto vaikuttaisi tilastollisesti merkittävästi älypuhelimen käytön muutokseen. Tuuppaukset, jotka paransivat joko kykyä, motivaatiota tai tavoitteen saavuttamista aiheuttivat tilastollisesti merkittävän käyttäytymisen muutoksen.

Havaittiin, että tutkimusjakson jälkeen älypuhelimen käytön tunnusluvut palautuivat kontrollijakson tasolle tai jopa korkeammalle tasolle. Lisäksi älypuhelimen vilkuilu ja yksittäisen puhelun käyttötapahtuman pituus kohosivat tarkkailujakson aikana tuuppausjaksojen aikaisen tason yläpuolelle. Voidaankin päätellä, että yksilöiden tavoissa vastata tuuppauksiin on tilastollisesti merkitseviä eroja. Niille, joilla itsearvioinnin vertailuluku oli korkea, tuuppaukset saattoivat laskea puhelimen käytön päivittäistä kokonaisaikaa.

Avainsanat: psykoinformatiikka, päätöksenteon ilmiöt, riippuvuus, tuuppaus, älypuhelin

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1 Introduction

This chapter provides an introduction to the thesis. First, a short summary of related research background is introduced, followed by the research problems of this thesis. Further, the scope and objectives of this thesis are described. Finally, introduction summarises the research approach and outlines the structure of the paper.

1.1 Background

The importance of smartphones in people's lives have become significant in the course of time. Smartphone usage cannot any longer be considered only a necessity, but the use has evolved into a habit which can lead to compulsive use and addiction (Lee, Chang, Lin & Cheng 2014b, 373). According to a panel research report on smartphone usage, the average amount of time spent using smartphones per day almost doubled, from 98 minutes in 2011 to 195 minutes in 2013 (Scott & Sale 2014). A research focusing on WhatsApp usage reported mean daily smartphone use of 161.95 minutes (Montag et al. 2015b, 3), and the average smartphone usage time amongst primary and secondary schools in Hungary have been reported to be as high as 4,48 hours per day (Körmendi 2015).

Using mobile device frequently and at excess durations can lead to various types of symptoms both in personal as well as working life. It has been proposed that some people may have a problem letting phones and their notifications go unnoticed for a period; responding to the stimuli flowing in can be seen as a form of a "contemporary multitasking" (Krishnan, Kurtzberg & Naquin 2014, 192). Using phones in excess quantities in personal business situations has also been shown to result to lower quality outcomes in negotiations, and to give a less trustworthy and less professional impression (Krishnan et al. 2014, 203). In addition of overall addiction, this increased use of smartphones has been shown to lead to many problems, including reduced concentration level during school classes and unsafe driving habits (Hong, Chiu & Huang 2012, 2152).

A specific sign of smartphone addiction, extremely frequent phone use, has been in the focus of scientific research. Classification of this type of use has been performed using criteria known from pathological gambling analyses (Leung & Liang 2016, 4-5). Internet addiction, a similar form of technological addiction, has been categorized as a type of "substance related and addictive disorder" (Lin, Chang, Lee, Tseng, Kuo & Chen 2014, 1). While smartphone can be an object of addiction, researchers (Hong et al. 2012, 2153; Lin et al. 2014, 3; James 2012, iii) have also used terms such as maladaptive mobile phone usage, problematic cell phone use, or problematic use of mobile phone to characterize abnormal smartphone usage patterns.

Phone has become an item frequently carried along: 90% of the U.S. adults owning a cellular phone have their phone frequently with them (Rainie & Zickuhr 2015, 2). As nearly 40 percent of people's online activity (Kim 2013a, 9), including games, social networking, media consumption and chat, originates from their mobile devices (Kim 2013b, 500). Therefore, it is not justified to classify the excessive smartphone use only based on measures of addiction.

Number of research reports indicate that the smartphone use is characterized by frequent, short sessions (Oulasvirta, Rattenbury, Ma & Raita 2012, 109). As an example of intermittent glancing, it has been reported that workers check for new emails every 5 to 10 minutes (Misra, Cheng, Genevie & Yuan 2016, 278). In a research conducted using a smartphone application, "psych app", installed to the smartphone to recruit test subjects, conduct psychological research and to collect research data, the daily usage count was 73.1 ± 43.8 times (Lin et al. 2015, 142). While this repeating behaviour can be disturbing to the social relationships, and people generally find phone usage distracting in the social setting, 89% of the surveyed people reported to have used a phone themselves during their most recent social gathering (Rainie et al. 2015, 3–4).

Several studies have been connected the amount and frequency of smartphone use to the indicators of certain types of addiction, and some studies (Lin et al. 2015; Hong et al. 2012; Lin et al. 2014; Leung 2008; Foerster, Roser, Schoeni & Röösli 2015) indicate that the compulsive use of smartphones share the characteristics of drug and alcohol addiction, and internet dependency. Some research reports (Lin et al. 2014, 4; Gökçearslan, Mumcu, Haşlaman & Çevik 2016, 647) suggest validating the findings by way of an application that records frequency and duration of the real-time smartphone use. Number of reports include recommendations to inform individuals of their inclination to compulsive use, so that the individuals can learn self-control for proper smartphone usage (Lee et al. 2014b, 378–379; Leung 2008, 109).

Although different forms of problematic behaviours resulting from the pervasive smartphone use has been extensively reported, the prevention of the originating behaviour has gained only little attention. Even if smartphone addiction and internet addiction has been referred in the latest available edition of the Diagnostic and Statistical Manual of Mental Disorders warranting more clinical research and experience (Hiller 2013), it was not possible to identify researchers or research programs focusing on internet or smartphone addiction in Finland. Although models exist for planning and conducting behaviour change interventions, including Michie, van Stralen and West's (2011) Capability, Opportunity- Motivation – Behaviour (COM-B) framework, despite heavy efforts, it was not possible to find research reports that have focused on applying behaviour change interventions to lower smartphone with the help of nudges.

Due to these reasons, this topic was seen to warrant more research, especially connected to the behaviours of healthy test subjects. Laurea University of Applied Sciences (2016) states in its strategy for 2020, that its applied research promotes future well-being, and that the research is carried out with practical research and development. The pervasiveness of smartphone use, the increased concerns in the resulting symptoms, and the heritage in neuromarketing and behaviour change research in Laurea NeuroLab stimulated to investigate behaviour changes using nudges. Nudges are defined as changes in decision-making context that try to consistently guide people to make decisions that are better for them from their own point of view (Thaler & Sunstein 2008, 5–6). Success in this area can potentially promote well-being in people's lives both locally in Finland and globally, as well as expanded research evidence in behavioural economics.

1.2 Research problems

Some of the results from the previously studies (Tossell, Kortum, Shepard, Rahmati & Zhong 2015, 39; Montag et al. 2015b; Kim 2013a, 10; James 2012, 75; Oulasvirta et al. 2012; Oliver 2010; Lin et al. 2015) have suggested high frequency of use and high daily usage of a smartphone. However, it is hard to find research reports that had investigated the use of nudges to lower the smartphone use. In cases where the research objective was to lower the smartphone use, the results have almost exclusively been limited to the treatment of addiction for clinically assessed patients (Kim 2013b). The research reports in the scope of the literature review did not include such occurrences that would have applied nudges to direct users for proper smartphone usage.

While software developers have created free and commercial applications to enforce restrictions and curfew on the use of the smartphones and tablets, there are limited amount of applications that does not apply invasive methods to restrict smartphone use. The inherent problem in enforcing restrictions upon the use of smartphone lies in that the devices are bought for everyday use, and the users themselves may find little reason in enforcing hard restrictions on the use of the items that they have paid for. The Internet access and the cyberspace is considered as "an extension of the personal space", and an individual is generally trusted to make an independent choice of their usage limitations. (Manjikian 2016, 12.)

Where enforced restrictions and curfew may result to a decreased smartphone use, they do not educate users self-control for more responsible smartphone use. In fact, taking a wireless device ever for a short time can increase anxiety (Cheever, Rosen, Carrier & Chavez 2014, 295). In order to help people lower their smartphone use by way of voluntary measures, it is important to investigate how PSU can be influenced using smartphone application executing behaviour change interventions.

A concept of ‘nudge’ has been introduced in contrast to policies enforcing to a desired behaviour or to introducing significant economic incentives. Nudges can be used to design such decision-making environment that “alters people’s behaviour in a predictable way without forbidding any options or significantly changing their economic incentives” (Thaler et al. 2008, 6). These nudges have been introduced in connection with libertarian paternalism, according to which users are free to choose, but it is legitimate to try and influence people’s choices so that they would make better decisions “as judged by themselves” (Thaler et al. 2008, 5).

Nudges have been widely adopted in public policy-making, and there is a wide body of evidence suggesting their impact to people’s health and wealth (Johnson & Goldstein 2003; Keller, Harlam, Loewenstein & Volpp 2011; Kallbekken & Sælen 2013; Shu, Mazar, Gino, Ariely & Bazerman 2012; Schultz, Nolan, Cialdini, Goldstein & Griskevicius 2007). However, it has been hard to find any smartphone application that would make use of nudges to embrace people’s awareness towards their usages patterns without imposing a policy on their usage. Considering the prevailing evidence of the connection between amount of smartphone use and abnormal or addictive usage patterns, it is justified to identify ways in which the users of the smartphones can be nudged for proper smartphone use by way of a psych app.

In this thesis it was theorized that a nudge would generate an interest from the test subject in the beginning of the stage due to its novelty, but the novelty would vane in the course of time. As nudges relate to the smartphone use, the behaviour change would occur due to the test subjects’ capability to observe the behaviour, and make necessary adjustments to their smartphone use. In order to achieve a long-lasting reduction of smartphone usage level using nudges implemented in the smartphone software, a smartphone user should engage to a reflective thinking, and as a result of which, they should not use their phone when they would feel an urge to do so.

However, there is limited evidence available to prove that the behaviour change by way of nudging can be long-lasting (Allcott & Rogers 2012, 2). Available results indicate that in some cases the results of the efforts can decay, and the behaviour can return to the level before the treatment (Allcott et al. 2012, 3). To avoid creating excessively irritating smartphone user experience, and in order to associated nudges to a framework of behaviour change interventions, it is important to understand how each of the nudge contribute to the behaviour change, and whether the lasting effect of a behaviour change remain if the corresponding nudge is no longer in effect.

1.3 Scope of this thesis

This thesis focuses on the use of nudges to decrease Problematic Smartphone Use (PSU). The scope of the thesis is to investigate PSU perceived by the users, and how the frequency and the amount of smartphone use can be impacted by using different types of nudges presented in the smartphone screen. In the thesis, a set of interventions are constructed to test the response of smartphone users towards three types of nudges, and the absence of them thereof. The first Capability-nudge provides information regarding the phone use, the second Motivational-nudge provides information and an optional valentic emoticon based on the progress of the smartphone use, and the third Goal-attainment-nudge provides information and an optional valentic emoticon if the test subject has reached the pre-defined personal goal.

Together with two pro bono software developers that wished to remain incognito, a suitable smartphone application was developed to connect to the cloud computing infrastructure that executes the constructed experiments. Further, suitable descriptive and inferential statistical analysis methods were selected and used to analyse the data to derive the response of the smartphone users towards the nudges. Finally, by combining the field research with the self-assessment of the smartphone users' behaviours and reactions relevant to smartphone use, the scope of this thesis is to understand how people perceive their level of PSU.

While the psychology, and the aetiology of the Internet and PSU is intriguing, this field of study would require professional expertise in psychology and psychiatry. This thesis focuses on using nudges to lower smartphone use on healthy test subjects, and the psychological and psychiatric basis of Internet and smartphone addiction has been scoped out of this thesis. Earlier research results (Mueller, van der Heijden, Klein & Potters 2011; Altmann & Traxler 2014) have also shown that the effect of nudges do not significantly correlate with economic or sociodemographic variables. Therefore, associations to the sociodemographic background variables have been scoped out from this thesis.

1.4 Objective of this thesis

The objective of this thesis is to find out how PSU can be lowered with the help of nudges. In order to reach this objective, the thesis includes four research questions. These four research questions have been the basis for the experiment construction and the data analysis.

The first research question relates to this self-assessment, and it asks how the results of self-assessment are associated with the characteristics of smartphone use. The purpose of the thesis is to examine the association between self-assessment of the smartphone behaviours, and the actual smartphone use. The self-assessment combined with the results from the psych app helps gain insights on psychological constructs that can help people change their usage patterns and behaviours depending on the type of PSU they may exercise.

The second research question asks if the phone usage can be nudged to a lower level without using policies and coercive measures. The purpose of this research question is to investigate how nudges can be used to lower the smartphone usage in terms of frequency of use and total time spent on a phone.

The third research question asks if some nudges have stronger effect in influencing improper phone usage. This thesis examines how smartphone users respond to different type of nudges and how these nudges impact to their smartphone usage. It was assumed that the differences in the smartphone usage indicators are due to the type of nudge, and the results would indicate how nudges impact to the smartphone use. Where some of the nudges were designed to provide information pertaining to the smartphone use, or to help test subject assess the trend of their usage, the goal-directed nudge was also expected to reinforce commitment to strive for lower smartphone use.

Finally, the fourth research question asks if a permanent behavioural change can be maintained even if the nudge goes away. The purpose of this question is to examine if a long-lasting effect can be attained even if the nudge itself would go away.

This thesis aims to contribute to the growing evidence of the social implications of the use of mobile phones. Previously, this topic has been studied under the field psychiatry and psychology to develop methods to diagnose Internet and mobile phone addiction (Hong et al. 2012; Lin et al. 2014; Kim 2013b; Kuss, van Rooij, Shorter, Griffiths & van de Mheen 2013; Leung et al. 2016; Walsh, White & Young 2008; Beranuy, Oberst, Carbonell & Chamarro 2009; Lopez-Fernandez 2013; Lee et al. 2014b; Salehan & Negahban 2013; Lepp, Barkley & Karpinski 2014).

The results of this thesis can be useful to better understand how choice architectures developed according to libertarian paternalism can be introduced to the use of modern technology, and how users respond to the nudges compatible with it. This new information can be used to develop applications and methods to inform users of their maladaptive behaviours, enhance ways to embrace people to responsible phone use, and potentially find out solutions to avoid engaging to a phone usage when that would be professionally deficient or harmful. This could potentially help decrease the amount of people that later become subject to phone addiction.

1.5 Research approach

This thesis is based on four essential research approaches. First of them deals with the self-assessment of the smartphone addiction, and the second approach concerns about the design and execution of a behaviour change intervention using nudges as part of the psych app. The third approach relates to the use of psych apps to conduct the experiments and collect data from the research. Finally, the fourth research approach addresses the data analysis using psychoinformatics and big data.

Self-assessment criteria and scales have been developed to diagnose and measure smartphone addiction and abnormal phone usage (Salehan et al. 2013; Lee et al. 2014b; Foerster et al. 2015; Lin et al. 2014; Gökçearslan et al. 2016; Butt & Phillips 2008; Kwon, Kim, Cho & Yang 2013a), many of which focus on addiction indicators such as compulsive behaviour, functional impairment, withdrawal, tolerance. Many of these assessment scales have been developed in consultation with clinical psychologists and have been demonstrated to be appropriate tools for assessing smartphone addiction. A screening tool Smartphone Addiction Inventory (SPAI) (Lin et al. 2014) was chosen for the self-assessment, more specifically the short form of the questionnaire (SPAI-SF) with ten questions. These ten questions are designed to measure four addiction states: Tolerance, Withdrawal, Compulsive behaviour and functional impairment (Lin et al. 2014, 2). The reason of selecting this assessment scale was due to it having been earlier used in a research to identify smartphone addiction via a mobile application (Lin et al. 2015). The self-assessment was developed into the smartphone application responsible for the execution of the study, and once completed, the responses were stored to the cloud computing infrastructure for further processing. The self-assessment results were analysed using commonly available methods of inferential statistical analysis.

As a novel concept to study the use of nudges in lowering PSU, this study applies a framework of behaviour change interventions. The behaviour change interventions are constructed by using the COM-B framework. According to this model the behaviour change involves changing one or more of capability, opportunity and motivation that relate to the behaviour (Michie, Atkins & West 2014, 60). Capability refers to knowledge and skills that influence engaging in the activity, opportunity refers to everything outside the test subject that prompt for behaviour or make it possible. Finally, motivation refers to processes that energize and direct behaviour (Michie et al. 2014, 3–5). These interventions were constructed into the application used in the study, and the time stamps of the nudges were recorded into the data.

In order to better understand the correlation between the results of smartphone addiction scale and the real-life usage of a smartphone, a name “psych app” has been suggested for such applications that are used to run controlled experiments in the phone. These applications can for instance recruit test subjects, obtaining permission for the study, conducting the study and collecting the results. (Miller 2012, 221.) Several applications have been developed to monitor the phone use (Lin et al. 2015; Goedhart, Kromhout, Wiart & Vermeulen 2015; Oliver 2010; Lee, Ahn, Choi & Choi 2014a). These applications capture the events of the phone use, for example when user opens and locks the phone screen, or depending on the objectives of the research, events such as phone call times and durations, Internet links visited, or location of the phone. In this thesis the scope was limited to use only events that indicate the use of phone, including screen open and lock events. These events were stored to the cloud computing infrastructure for further processing.

Finally, to infer statistically reliable results, the data generated by the psych app must be pre-processed and analysed. The event data was copied from the cloud computing infrastructure to MATLAB application, and transformed to time-intensity domain. Using Hilbert-Huang Transform, the data processed using Empirical Mode Decomposition (EMD) until relevant intrinsic components (repeating usage patterns of specific session length) and residue (trend of the data) could be extracted for inferential analysis. This approach was selected due to earlier demonstrated use in a similar research (Lin et al. 2015, 140–142).

The research design used in this study was reviewed by the ethics committee of the Federation of University of Applied Sciences in Finland. The advices in the statement from the committee was used to ensure the confidentiality of the data that was collected, and to limit the interpretation of the results in the psychiatric and psychological context.

1.6 Structure of this thesis

This thesis is structured as follows. The first chapter introduces to the research area and specifies the research problem and objectives. The second chapter provides a literature review for the key theoretical frameworks: mobile phone addiction, nudges and behaviour change interventions, the use of psych apps and psychoinformatics, connected with the big data analysis. The theoretical framework is reflected against the research setting and the smartphone application used in the thesis.

The third chapter describes the research design, data collection and data analysis. The fourth chapter present the results of the self-assessment and the analysis of the collected and pre-processed field data. The fifth chapter discusses about the implications of the results and suggests statistical and scientific inferences, and examines them against past research in the area.

The final chapter, conclusion, answers to the research questions, discusses about the limitations of the study, and provides recommendations for further research.

2 Reviewing research on smartphone addiction, nudges and psychoinformatics

This chapter introduces the essential literature in the theoretical frames of references. Due to the nascence of nudges in researching addiction-related phenomena, and relatively novel characteristics of this study, the literature review has been extended to familiarise the reader with the new theoretical frames of references.

The first section introduces a concept of mobile phone addiction and explains why it is relevant in investigating the effect of nudges in lowering PSU. The second section examines research methods that make use of software installed onto the test subjects' wireless mobile devices. This section also analyses the self-reporting bias and identifies different ways to debias the test subject or expose these biases in the test data. The third section introduces relevant psychological approaches in human decision-making. The concept is then explained using Michie et al's COM-B framework.

Finally, a concept of nudges is introduced. This part is connected closely to the stages of the research, and adequate theoretical fundamentals are given for each of the stages.

2.1 A brief look into the mobile phone addiction

This section examines the field of Internet and smartphone addiction, and explains essential aspects of smartphone addiction. The section also examines rehabilitation approaches for smartphone addiction in order to explain why nudges can be a viable alternative to clinical rehabilitation.

2.1.1 Internet addiction and problematic use

Between the years 2005 – 2015, Internet access in the developed world has become ubiquitous. According to International Telecommunications Union, the United Nations specialized agency for information and communication technologies, in year 2015 81,3% of the households in developed world had Internet access. Active mobile-broadband subscription was with 86,7% of the population in the developed world and with 47,2% in the whole world. (International Telecommunication Union 2016.)

This development in the proliferation of Internet access has changed people's lives in many ways, and have resulted to increased economic and social benefits. According to Deloitte (2014, 3–4), access to weather conditions and wholesale prices amongst Indian farmers and fishermen have increased the profits by 8%, and decreased consumer prices by 4%. Deloitte have also estimated that by extending Internet access in developing countries to the level that of developed countries, the living standards and income could rise by up to 600 US dollars per person.

However, the Internet access has not only provided positive outcomes. Health, psychologic and psychiatric professionals have expressed concerns over the “relationship between Internet use and psychosocial wellbeing” (Caplan 2002, 554). While addiction is traditionally associated with the dependence on a physical substance, research suggests that the definition should also account for the behavioural patterns (Leung 2008, 94). Regardless of whether the behaviour under investigation is classified as dependence or addiction, Caplan (2002, 555) refers to earlier studies pointing out that there are people developing a harmful dependence on the Internet.

The abnormal Internet usage has been characterized as an inability to control one’s Internet use even if it inflicted negative implications to the psychological, social, school and work – a type of impulse control disorder (Spada 2014, 4; Lopez-Fernandez 2013, 2; Leung et al. 2016, 3). While it has been suggested that the Problematic Internet Use (PIU) is a medium to fulfil other types of addictive behaviour, there is a debate between researchers if there is an additional, distinct form of addiction (Spada 2014, 4; Yau et al. 2014, 14). Davis (2001, 188) distinguishes PIU into specific and generalized PIU.

Where specific PIU refers to a form of an addiction where Internet acts as a medium to a particular purpose, such as online sex or online gambling, generalized PIU can be seen as a “multidimensional overuse of the Internet” (Davis 2001, 187–188). According to Davis, generalized PIU does not necessarily have a clear objective, but is associated with social activities one can perform in the Internet. Davis’ (2001, 193) cognitive-behavioural model suggests three symptoms and consequences resulting from generalized PIU. Firstly, affected people have cognitions that can be obsessive thoughts about the Internet, diminished control of impulse towards online activities, and guilt about online use. Secondly, PIU results to specific behaviours, such as checking emails number of times per day, or spending excess time in the discussion fora. Finally, in the course of time, generalized PIU can result to negative outcomes, such as increased social withdrawal.

Davis (2001, 193) points out that the nature of the generalised PIU is associated with Internet as such, rather than using Internet as a mean to practice another addiction. Salegan & Negahban (2013, 2632) have suggested that one reason of this addiction can be derived to the theory of optimal flow by Csikszentmihalyi. According to the researchers, some individuals might find Internet usage so enjoyable, that “that they will try to maintain the state even at high costs". As this type of problematic use is proposed to be particularly harmful to the society, it is recommended that the ramifications of Internet abuse cannot be dismissed as something that would resolve on its own (Davis 2001, 194; Kuss et al. 2013, 1988).

When internet addiction literature is examined, one is hard to avoid noting the underlying criticism for example presented by Caplan (2002, 555). The writer refers to other scholars, citing that "many published articles contain information that has not been empirically researched. . .[or]. . .review findings in the current literature but provide no independent empirical support." It is worth noting that the research efforts have almost exclusively focused on the PIU with diagnosed patients treated with rehabilitation or medication (Kim 2013b; Spada 2014).

Due to this proposed lack of empirical evidence of the PIU it would be reasonable to investigate how generalized PIU is visible in the real life of the healthy test subjects before the internet addiction has been escalated to a level requiring treatment. Nielsen (2016) reports that people in the United States of America spend more time in the Internet using their smartphone than by any other device. It is therefore relevant to extend the scope of generalized PIU into the investigations of PSU. To investigate if less invasive measures could be applied to lower the cognitions, behaviours and negative outcomes, the nudges were included into this thesis. The effect of nudges may have a potential to address early stages of PSU, as well as to guide people for right behaviours in their personal and professional social situations.

2.1.2 Fear of Missing Out

Davis refers to the social aspect of the generalized PIU. According to the cognitive-behavioral model of the writer, "the need for social contact and reinforcement obtained online results in an increased desire to remain in a virtual social life" (Davis 2001, 188). This online presence can also be observed in other fields of research dealing with people's dependencies on mobile devices to stay connected with what others are doing (Przybylski, Murayama, DeHaan & Gladwell 2013, 1841). This phenomenon is called Fear of Missing Out (FoMo) or Nomophobia (Cheever et al. 2014, 291).

According to the definition of FoMo, people have dependence on their mobile devices because of their "pervasive apprehension that others might behaving rewarding experiences from which one is absent" (Przybylski et al. 2013, 1841). This expectation of an important social occurrence can distract people from their social experiences that are available in their here-and-now (Przybylski et al. 2013, 1842). It has been suggested that the proliferation of mobile devices have created an expectation that people are available at all times. This further increases mobile phone use, resulting to a communications overload that ultimately creates guilt, resentment and stress due to the inability to tell unimportant and important messages apart, and respond to the communication requests. (Cheever et al. 2014, 291.) Research on the social behaviour of mobile users has pointed out that people embrace split consciousness where people are physically present but are engaged in a virtual reality and the social situations in there, having to manage multiple social norms from the concurrently present worlds – also referred as a state of poly-consciousness (Misra et al. 2016, 279, 291). In some cases people have been observed to check their phones every 3 to 5 minutes regardless of whether the phones evoked any indication of network activity (Misra et al. 2016, 280).

FoMo has been shown to relate to the greater engagement in the social media (Przybylski et al. 2013, 1846). It has been shown that about 20% of the smartphone usage can be accounted for the use of WhatsApp, and less than 10% is accounted for the use of Facebook (Montag et al. 2015b, 4). Further, it has been suggested that the use of social networking on a smartphone can predict mobile phone addiction (Salehan et al. 2013, 2636). While it may be hard to prove the inverse correlation, that the increased frequency of social media would explain FoMo, one could expect that people who frequently engage with their smartphone are doing so in order to stay in connection with people not here-and-now. To help people focus on the real-life social relations, it is reasonable to understand if nudges could influence to the frequency of smartphone use when people are seeking for social contact in the Internet.

2.1.3 Smartphone addiction and problematic use

In the recent years, smartphones have developed to a point that they are legally regarded as computers. This development has allowed people to consume essentially services known from their computer from their smartphones. However, the general availability of high-performing smartphones and related services, the development has not only been positive. The use of phones has been connected to decreased physical fitness, as well as generalized PSU and mobile phone addiction. (Lepp et al. 2014, 343; Hong et al. 2012, 2152–2153.)

Although extensive studies have been performed to investigate PIU, very little number of research reports have been published regarding smartphone addiction. In one research report 16,9% of the test subjects were observed with smartphone addiction (Haug, Castro, Kwon, Filler, Kowatsch & Schaub 2015, 303). Smartphone addiction has been regarded as similar to general Internet addiction, rather than specific addiction such as gaming. This has been explained by the fact that the smartphone use is characterized by the use of multiple applications. Addiction is therefore not compliant with the definition of specific PIU as defined by Davis. (Lin et al. 2015, 143.)

Kuss et al. (2013, 1993) have found that when people used their phones in their kitchen where Wi-Fi network were available, the likeliness of being addicted to the Internet was elevated compared to those who did not have equally extensive Internet access. Considering the earlier mentioned increase in the mobile broadband penetration, this result would suggest that the likelihood for Internet addiction could increase as more people have permanent Internet access from their phones.

It has been claimed to still be unclear why people do not apply self-control to limit inappropriate and improper smartphone use. Amongst other characteristics typical for other types of addiction, smartphone addiction has been reported to include for instance preoccupation with mobile phone, increased amount of time to achieve satisfaction, unsuccessful efforts to control the amount of smartphone use, or an irritation when an attempt has been made to reduce the use of smartphone (Leung 2008, 94). When addiction has been connected to the usage patterns of the phone, the frequency of the phone use has most significantly associated with the smartphone addiction (Lin et al. 2015, 142). This is compatible with indicators of internet addiction, according to which a high frequency use of specific application increased the risk of being addicted to the Internet (Kuss et al. 2013, 1992; Lee et al. 2014a, 9). In another research, if the mobile phone was repossessed from the test subjects', those individuals expressed higher level of anxiety that used the device more frequently (Cheever et al. 2014, 295).

It has alternatively been proposed that smartphones are rather habit-forming than addictive. According to a research suggesting this theory, smartphones can offer quick access to activities that are rewarding, such as news or social networking. Additionally, some habits become automated and partly exist to cope with boredom and lack of activities in the real life. The researchers found that the number of smartphone sessions were substantially higher than the laptop sessions. This was explained by their constant presence and plethora of different channels to connect to remote information. (Oulasvirta et al. 2012, 107–108.)

Even though it may not be unambiguous if high frequency of smartphone use should be considered as an addiction or a habit, the research reports consistently suggest that high frequency of smartphone use disrupt daily routines and decrease efficiency. Where Oulasvirta et al. (2012, 105) suggest that the frequent phone checking is not perceived as problematic, but "at worst, slightly annoying", Lin et al. (2015, 144) suggest that frequent short smartphone sessions can interfere with the normal routines even if the conditions were hazardous. This is suggested to be "similar to the criteria for substance related disorder" (Lin et al. 2015, 144). Lee et al. (2014a, 7) attribute short frequent sessions to the social network and chatting applications, and suggest that these "can be considered as key addiction applications".

2.1.4 Diagnostic criteria for Internet and smartphone addiction

Discussion to formally document Internet addiction in the universal literature and handbooks in psychiatric diagnoses started in 1995 (Saliceti 2015, 1374), and the discussion have so far addressed both reasons to include as well as more neutral approach (Block 2008; Pies 2009). While no conclusion on formal recognition of the addiction have been reached in Western countries, Internet addiction has been officially recognized in China. Respective methods have also been published to diagnose patients of their internet addiction. (Manjikian 2016, 2.)

The first test to measure internet addiction is attributed to Dr. Kimberly Young (Manjikian 2016, 1) and the Diagnostic Questionnaire (DQ). The purpose of the study including the test was to “determine a set of criteria which would define addictive from normal Internet usage” (Young 1998, 238). In the discussion of this report, Young shares numerous observations that are repeated in the later research reports concerning the diagnostic criteria for Internet addiction. This list includes inability to moderate and control the Internet use, the interactive characteristics of online activity, influence to academic or work performance, and influence to social relations.

Young’s DQ was broadly adopted and refined in the years following its release (Montag & Reuter 2015c, 14), and it also was the foundation in the first smartphone addiction test, Smartphone Addiction Scale (SAS) (Kwon et al. 2013b, 5). This test was executed as a 48-item questionnaire, and it identified six factors of addiction: Daily-life disturbance, Positive anticipation, Withdrawal, Cyberspace-oriented relationship, Overuse and Tolerance. While number of identified factors differ between studies, similar causes have been identified in several addiction tests pertaining to time management problems, negative outcomes in academic or work performance and compulsive use (Hong et al. 2012, 2154; Caplan 2002, 563–564; Leung 2008, 100–101; Walsh et al. 2008, 83–88; Foerster et al. 2015, 281; Lin et al. 2014, 4). Some concerns have also been expressed concerning the validity of different addiction scales (James 2012, 62–63).

Young (1998, 243) has argued that people with Internet addiction have become addicted in the same way that people who become addicted to drugs, alcohol or gambling. His diagnostic questionnaire used the same cut off score than that of criteria for pathological gambling. Number of behaviours have been associated with each of the factors of smartphone addiction. Pertaining to functional impairment, Young has reported the use of Internet to the point where daily activities were ignored, and the Internet usage have occurred harmful repercussions to relationships with family and friends. The addicted individuals were lying the amount of time and money they consume to the Internet activity. Compulsive use can be observed from the reaction of addicted Internet users as soon as the overuse is brought to discussion. The subjects deny their compulsion, and engage to lying regarding the amount that they use Internet. The excessive tolerance to Internet use have been seen when people have forcibly kept themselves awake, and at times they have been unable to perform their daily duties due to the exhaustion. Addicted people also engaged in extensively long sessions in the night-time, while being aware of their obligation to go to work or to school in the morning. Attempts to withdraw from Internet usage was reported to occur cravings and other withdrawal symptoms, and subjects found it hard to live without Internet despite their acts to prevent themselves from using Internet. (Young 1998, 243–245; Young 2004, 405.)

The Revised Chen Internet Addiction Scale has suggested four factors for the Internet addiction: compulsive use and withdrawal, tolerance, interpersonal and health-related problems, and time management problems (Mak et al. 2014, 1241). Smartphone addiction inventory builds on the predecessor of this scale, and uses four factors: compulsive behaviour, functional impairment, withdrawal and tolerance (Lin et al. 2014, 2–3).

Lin et al. (2014, 4) discuss about the methodological limitations of their study. While the authors suggest that the SPAI "is a valid and reliable self-administered screening tool to identify smartphone addiction", they further note that the self-reported results should be concurrently validated for example by using an application that record the frequency and duration of the smartphone use.

An email correspondence was conducted with the authors of the original SPAI research (Lin et al. 2014), Yu-Hsuan Lin and Sue-Huei Chen. As a result of this correspondence the short form of SPAI, SPAI-SF was selected as a scale to be used in this thesis, augmented with results generated by an application similar to that of presented by the partly same research group (Lin et al. 2015). This is the first thesis in which SPAI-SF is known to be used to measure behaviours related to smartphone addiction. Despite heavy efforts, no such reports could have been found where the focus has been on lowering PSU for healthy test subjects. Due to this reason, this study has been constructed based on Lin et al.'s suggestion. Additionally, the psych app used in this thesis includes nudges to investigate their effect in lowering PSU amongst healthy test subjects.

2.1.5 Treatment and prevention of smartphone addiction

The treatment of internet addiction (and smartphone addiction thereof) is considered non-trivial and little research has been conducted on the topic. Kim (2013b, 501–503) reviews various methods that could be applied for addiction treatment, and argues that the smartphone addiction is "not a personal problem", and that a solution should be found for the smartphone addiction rehabilitation in a [South-Korean] national level. According to the writer, smartphone addiction treatment is categorized to behavioural treatment and complementary treatment. Behavioural treatment includes various psychological therapeutic methods applied to the problem. Complementary treatment focus on the environmental factors in order to improve the overall well-being of the addict.

It has also been reported that individuals with internet addiction are resistant to treatment and tend to relapse at a high rate (Block 2008, 306). While rehabilitation techniques include relapse prevention, it is hard to find any literature that would deal with the prevention of smartphone addiction or PSU in the first place. A research conducted in South-Korea includes a quasi-experimental study that focused on providing information about internet addiction. The results of the research suggest higher self-regulation and lower score for internet addiction self-diagnosis, as well as lower internet usage time. (Mun & Lee 2015.)

Literature provides little documented results concerning the preventive treatment of internet or smartphone addiction, and of PSU. The focus of the literature is rather almost exclusively on the treatment of internet addiction after the psychologic or psychiatric diagnosis. As there is little documented evidence on the effects of preventive treatment for smartphone addiction or PSU, it would be reasonable to investigate the effects of preventive and non-coercive measures towards healthy, undiagnosed people.

It is debatable if economic benefits could be provided to the national economy and if the costs of providing healthcare could be lowered if smartphone use could be decreased before it becomes addictive. Finally, as the preventive measures would not necessarily have to be based on practices from psychiatric and psychologic frames of references, examining the influence of active reflection into the frequency and amount of smartphone use could eventually help develop ways to lower smartphone use.

2.2 Nudges in researching Problematic Smartphone Use

In this section the reasons to investigate the effect of nudges to lower PSU are argued. The definition of the term Nudge in the context of libertarian paternalism is examined, and it is investigated how different psychological frames influence to the decision-making process, as well as how these psychological frames define the experimental conditions in this thesis.

2.2.1 Behavioural economics and nudging

For decades in the 20th century, Amos Tversky and Daniel Kahneman worked on their research programs in order to explore the heuristics and biases that are present when people make decisions. The current understanding in which people engage a dualistic system with two modes of thinking and deciding is based on this body of work. So-called System 1 is characterized as an automatic, effortless thinking, often influenced by habits that cannot be influenced easily. System 2 is described as effortful, deliberately controlled thinking that is associated with computations and complex operations (Kahneman 2003, 1449–1450, 2013). Although people were asked to work accurately on the task, the limited capacity of mental effort, also known and bounded rationality, results to preferring an intuitive, fast-operating but slow-learning cognitive system to apply heuristics such as prediction and intuition.

The dualistic system suggested by Kahneman and Tversky also includes biases such as neglect or insufficiency in weighing probabilities, or using lifelong experience as a basis of determining the outcome. As an outcome, many decisions are based on beliefs and subjective assessment of probabilities of possible outcomes. (Tversky & Kahneman 1974, 1124.)

The works of Kahneman and Tversky have eventually amalgamated into behavioural economics. In this thinking, intuitive cognitive system is present with its inherent heuristics and biases, resulting to anomalies in people's behavioural patterns. (Kao & Velupillai 2015, 242–244.) Behavioural economics examine these anomalies from different point of views, including risk, time, strategizing and prosociality, all of which will can lead to different outcomes than when behaviours are evaluated by using classical economics theories.

Behavioural economics acknowledge complexities of different types. Complexity in evaluating risk refers to human's tendency to adapt to their current state, neglecting the full probability of the risk associated with the option compared to the other options. Complexity with time refers to people's tendency to value future rewards according to a hyperbolic function, effectively overweighing options closer to their present time. Complexity with strategizing refers to people's limited ability to assume and analyse other people's intentions and acts due to their focus on the possible payoffs. Complexity with prosociality refers to the influence of motives that do not stem from a pure self-interest. (Kahneman 2003, 1450–1451; Camerer 2014, 867–870.) The presence of these complexities act as a basis for designing such decision-making contexts where people could consistently make predictable choices due to the factors present in the context (Thaler et al. 2008, 3).

In this thesis, it is assumed that smartphone usage is partly influenced by these anomalies and complexities in decision-making. It has been discussed before in this report that people's behaviour can have characteristics resembling addiction, or that their smartphone behaviour can cause negative implications to their social situations and relationships. However, it may be that the individuals may not be fully aware of the implications of their behaviour, or that they reject to take action to mitigate this behaviour despite their knowledge.

In order to occur a change in a smartphone use, a behaviour change needs to occur. Michie et al. (2011, 2) have suggested a definition for behaviour change intervention, stating that it is a "coordinated sets of activities designed to change specified behaviour patterns". This definition broadly complies with the definition of nudge from Thaler and Sunstein. Where nudge is defined as an attribute in the environment influencing to the behaviour, described as a change in the token of behaviour, Michie's definition calls for more active role for the subject, described as a change in the type of behaviour.

In this regard, Michie et al's definition is closer to Hansen & Jespersen's (2013, 18) transparent nudge, conveying the underlying intention, as well as how the change is pursued. Hansen and Jespersen (2013, 19–20) propose a specific type of nudge engaging reflective system of the person while exposing the intentions and means by which the nudge attempts to make a behaviour change. Amongst other types, writers provide examples of this type of nudges that either make actions salient, make preferences salient, or by making subjects to commit to an objective.

One aspect of PSU can be interpreted from the point of view of Akrasia. It has been argued that people perform uncompelled actions intentionally while they concurrently can argue good reasons for not performing these actions. According to O'Connell, people are frequently returning to their uncompelled behaviour even if they were willing to change their behaviour for better. (O'Connell 1996, 94.) This phenomenon has been known from the times of Socrates, and evidence shows that early thinkers contemplated on the underlying processes that inflict this behaviour (Dijksterhuis 2014, 508).

Akrasia, introduced earlier, can be in the context of PSU understood as an inability to correct malignant behaviour due to the insufficient clues in the decision-making environment, or an immediate gratification exceeding the resulting consequent suffering. It was not possible to find prior research evidence to explain if smartphone users would be engaged to an active reflection of their behaviour, if they were presented with information or an otherwise relevant content that quantifies their smartphone behaviour.

In the context of PSU, it can be argued if a given event of a smartphone usage is seen as an intertemporal decision: the use of smartphone right now is seen as more important than dealing with the consequences of its use in the future. O'Connell proposes that people may find their motivation to violate their commitment towards better behaviour if the attention is drawn to the akratic activity due to their insufficient self-control techniques (O'Connell 1996, 95). By applying O'Connell's approach to PSU, the interpretation would suggest that the PSU results from consciously maintaining improper use while being aware of the distinction between proper and improper use. The alternative interpretation could be that the problematic use is due to the absence of salient metrics, and due to this it is easier for the smartphone usage to become a habit.

Habits are explained as automatically triggered actions that have developed after a period of self-regulation of a behaviour. Repetition enforces habits becoming automated, and it has been proposed that automated habits can happen outside of conscious awareness. (Kwasnicka, Dombrowski, White & Sniehotta 2016, 10.) In the context of smartphone use, Oulasvirta et al. provided evidence that smartphones are "habit-forming" and that the intermittent use of smartphones can be seen as a checking habit: "a brief, repetitive inspection of dynamic content quickly accessible on the device" (Oulasvirta et al. 2012, 105).

From a behavioural economics perspective, checking habit can be seen to influence to a preference order in the decision. Even though a smartphone user might not expect an important content from their smartphone, the fear of missing out might bias the decision-making situation. Despite their potentially conscious preference of doing less with their phone, the automatic thought process overrides reflective system. Due to the bounded rationality and biased decision-making situation, automatic checking habit is a stronger behaviour than engaging reflective system to maintain sound phone usage habit.

Considering that smartphones are evidently habit-forming, they do not provide adequate information to guide usage towards responsible, non-addictive behaviour, and that substantial evidence has been provided for the harmful repercussions of addictive or PSU, a need arises to change the decision-making environment to encourage people for smartphone behaviour that is better from their own point of view. Part of the behavioural economics is to "prescribe ways to construct choices to help people of average mental skill avoid making bad decisions, while preserving freedom of choice for people who are confident that they don't make mistakes" (Camerer 2014, 870). The next subsection includes examination how nudges can be embedded into smartphones to change the usage behaviour.

2.2.2 Libertarian paternalism and nudging

Thaler and Sunstein (2008, 5–6) discuss about the freedom of choice with a desire to help people live longer, healthier and better. According to the writers, people should maintain their freedom to do what they like, while at the same time private institutions and governments should have right to steer people towards choices that improve their lives. As it has been shown that the anomalies in people's behaviour lead to decisions that are not best for people themselves, these partially conflicting aspects come together in libertarian paternalism. According to libertarian paternalism, all options are kept available without blocking or significantly burdening them, but the decision-making context is modified in a way that predictably alters people's behaviour towards the option that is considered the most optimal from their point of view.

Nudges are such changes in decision-making context that do not prevent any other option, or make fundamental changes to the economic incentives, but try to consistently guide people to make decisions that are better for them from their own point of view (Thaler et al. 2008, 5–6.) To be compliant with the underlying promise to freedom of choice, the nudges should be designed in such a way that those who, regardless of the nudge, decide to choose otherwise can do so with minimal cost and effort (Thaler et al. 2008, 13).

Ample evidence has been provided of the effect of nudges. Goal setting combined with a commitment, and feedback concerning the behaviour has been shown to lead to behaviour change. To reduce household energy consumption, different type of nudges has been shown to have different effect. Where providing information have improved knowledge about the issue, the behaviour change has resulted from tailored information, goal setting and feedback. Whether the goal has been set by an external party or the subject themselves, have not been shown to have influence. (Abrahamse, Steg, Vlek & Rothengatter 2007, 266, 273.)

Already in the cover page of the book, Thaler and Sunstein (2008) categorize the type of nudges to those dealing with money, those dealing with health, and those dealing with freedom. Hansen and Jespersen (2013, 14–18) have later evaluated the original definition of nudge, and proposed a framework consisting of four types of nudges. In this model, each nudge is categorized based on whether it stems from automatic (type 1) or reflective (type 2) thinking, and based on whether the intentions and means are exposed to the subject (transparent) or they cannot be reconstructed from the situation (non-transparent).

In Hansen and Jespersen's (Hansen et al. 2013, 20–27) categorization, type 1 non-transparent nudges are seen to manipulate behaviour, and are regarded as paternalistic interventions.

Type 2 non-transparent nudges are seen as regarded as invasive manipulations of choice without exposing the end to the subject, while at the same time imposing the responsibility of the choice to the subject. Type 1 transparent nudges are seen to influence people’s automatic behaviour, but as the subjects cannot fully avoid the effect, these are not regarded as truly libertarian. Finally, the writers introduce type 2 transparent nudges that try to influence such behaviours that result from people’s reflective thinking. These “empowering” nudges are seen to include the freedom of choice, and can be regarded as libertarian due to the subjects’ possibility to choose otherwise.

Hansen and Jespersen (2013, 13) explain the psychological foundation for each of the type of nudges using the dual process theory by Kahneman and Tversky. Based on this foundation, the writers suggest that part of the influence from type 1 nudges stems from manipulating the habits of the people. As suggested by Oulasvirta et al. (2012, 107), the checking-habit of smartphone users are triggered by cues outside the device, including situations and emotional states. Once the checking habit has triggered, the report suggests that the subsequent phone use will ensue from unlocking it. Consequently, in order to effectively influence to the choice situations with type 1 nudges, it would be justified to influence to individual smartphone users so that they would not regard the cues outside the phone as triggers to open their phones. Oulasvirta et al. (2012, 113) also referred to an option to place behavioural triggers in the smartphone display. Previous research projects had explored a glanceable display that presents user activity onto the phone screen. The results suggest that salient information with progress indicator promotes automatic goal activation (Klasnja, Consolvo, McDonald, Landay & Pratt 2009, 339).

2.2.3 Behaviour change interventions and nudging

Hansen and Jespersen’s (2013) categorization of different nudges provide a noteworthy framework to evaluate models of behaviour change. Michie et al. (2011) have presented a COM-B model where capability, opportunity and motivation influence to each other, and eventually to a human behaviour. Any intervention can impact to one or more of these components, potentially leading to a behaviour change. This subsection synthesizes different theoretical frameworks to provide a background for the basis of the nudges used in this thesis.

Michie et al. (2011, 3–5) explain each of these components. Capability refers to individual’s psychological and physical capacity, including knowledge and skills to engage in the activity. Opportunity consists of all the facts outside the subject, that make the behaviour possible or prompt for it. Motivation refers to the brain processes that energize and direct behaviour, including reflective decision-making and emotions, but also processes that are based on habits.

When nudges aiming to occur a behaviour change in smartphone is reflected to Michie et al's model, certain observations can be made.

Firstly, the influencing to the capability component of the COM-B can be seen as an awareness and salience of a given smartphone behaviour. If a person is oblivious to the problematic behaviour, or there are no visual indicators depicting the said behaviour, there is little basis for change. Therefore, all the nudges that aim to influence to the capability in the COM-B model should focus on increasing the knowledge of the smartphone usage, compliant with Hansen and Jespersen's type 1 transparent nudges.

Research evidence suggests that people's behaviour can be changed by making information salient and visible (Thaler et al. 2008, 71). This can be due to the availability heuristic, according to which people estimate frequency or probability based on how easily they can remember instances or associations of a said phenomenon (Tversky & Kahneman 1973, 208). If the recallability is enhanced, even by repeating the exposure to the information, the information can influence to the decisions related to the information (Tversky et al. 1973, 221–222).

Earlier research evidence states that the information in itself has modest, or at times unintended impact for behaviour change (Dolan, Hallsworth, Halpern, King & Vlaev 2010). In the case of nudging people to eat more healthily, the calorific information did not have a detectable change to the calories purchases, probable due to the fact that people did not know if the amount of calories they purchased and consumed was good or bad. (Elbel, Kersh, Brescoll & Dixon 2009, 1117–1118.) A regression study has proposed that at least 80% of the factors influencing environmental behaviour did not result from knowledge or awareness (Kollmuss & Agyeman 2002, 250). Even if the type 1 transparent nudge have been sufficient in changing smartphone behaviour, it remains unclear whether this type of nudge alone can occur a behaviour change.

Secondly, motivation component of the COM-B model can be seen as everything that quantifies a behaviour and exposes the preference of a given behaviour. This preference can come from outside, depicting the desired behaviour, but it can also be a self-defined goal defined by the person itself. (Michie et al. 2011, 4.) In the case of nudges to influence to smartphone use, this essentially requires knowledge of a given behaviour, which is further augmented with additional information that specifies the rating of the behaviour. This component should be examined from two point of views.

The first of the point of views is an externally evaluated injunctive valuation. From this point of view, an external authority defines the thresholds for good or bad behaviour, and provides an evaluation to the subject. Schultz et al. (2007, 430–432) have provided evidence that when the injunctive message was added to the feedback about the household energy consumption, the energy consumption was kept at low rate instead of regressing back to higher level, as well as provided a significant continued decrease in energy consumption. The injunctive emoticon can be interpreted as an attainment of or failure to attain desired behaviour, which may prevent relapse to the previous behaviour. While Schultz et al. (2007, 430–432) demonstrated the effect of both positively and negatively valenced injunctive emoticon, earlier research on motivation and competence has shown that positively valenced feedback enhance intrinsic motivation of a subject relative to no feedback, and that negatively valenced feedback decreased intrinsic motivation relative to no feedback (Deci & Ryan 2000, 234–235). Alcoholics Anonymous, a group focused to help recovering alcoholics stay sober focus on positive feedback and express their goal attainment by keeping count of days the individual has stayed sober (Fishbach, Eyal & Finkelstein 2010, 519). Where it has been shown that positive feedback is effective when actions signal commitment, it has been demonstrated that negative feedback is more effective in cases where actions signal progress (Fishbach et al. 2010, 520). Based on this framework it would be recommended to only show positive feedback provided that the research measures goal commitment (i.e. striving to use phone less) rather than goal attainment (i.e. the commitment to strive for the goal is not under debate, but the motivated individual wants to reach the goal).

The second point of view to motivation component is self-defined goal. It has been suggested that by measuring people's intentions, they become more likely to behave according to their answers (Thaler et al. 2008, 70). Locke & Latham (2002, 706–708) have suggested that there are four mechanisms by which performance in goal-setting is affected. Firstly, by directing attention and effort towards it. Secondly, by energizing to exercise greater effort to reach the goal. Thirdly, by increasing persistence to work towards the specified goal. And fourthly, by leading to the use of knowledge and strategies that help attain the goal. For people to strive towards the goal, the system shall provide feedback regarding the progress.

Research evidence have demonstrated the effectiveness of goal-setting in energy consumption (Abrahamse et al. 2007; Schultz et al. 2007). This effectiveness can be interpreted by using Kahneman's reference-dependence framework. According to Kahneman, people evaluate choices by using status quo as a reference point (Kahneman 2003, 1457). Schultz et al. propose that people evaluate descriptive norms as standards that they do not want to deviate from, and evaluate their behaviour by the distance from the norm (Schultz et al. 2007, 430). Even if Schultz et al. refer to social norms, there is little evidence that this effect does not extend to personal norms. It can therefore be proposed that by establishing a decision-making context where subject is constantly assessing their current situation against the situation where a goal has been reached could help people maintain their goal-attainment. It should be examined if this could provide a viable framework for nudges used in this thesis.

Finally as defined by Michie et al. (2011, 8–9), opportunity contains physical world and social dimensions, and it is broadly defined as the context of the decision-making. The writers propose restriction as an intervention to reduce the opportunity to engage in the target behaviour (Michie et al. 2011, 7). This can be broadly perceived as a coercion or policy-making, and therefore is not compatible with the definition of libertarian paternalism. In the context of PSU, one approach to applying opportunity would be to experiment the effect of disabling all visual, tactile and audible notifications. As a consequence, the smartphone user would blind oneself from all of the incoming messaging and dynamic content. The effect of this intervention would be dependent of the willpower of the user to refrain from engaging with the checking habit and to endure the fear of missing out.

In order to build on this theoretical framework, it is recommended that the nudges used to try and influence smartphone usage takes into account both the classification of the nudges according to Hansen and Jespersen, as well as what is known of behaviour change from Michie, van Stralen and West's COM-B model. The COM-B model suggests an approach to limit the interventions to one or a few behaviours, and use incremental changes instead to trying to do too much too quickly (Michie et al. 2014, 41). Building on these recommendations, to firstly influence to capability component, the nudges should inform smartphone users of their behaviours by using nudges compatible with Hansen & Jespersen's definition of type 1 transparent nudges. Secondly, to influence to the motivation component, the nudges should provide injunctive valenced feedback regarding the behaviour. And finally, to influence to the motivational component by setting self-defined goal and providing feedback regarding the progress for goal attainment.

2.2.4 Behaviour change maintenance

It has been reported that Internet addiction has high relapse rates (Kim 2013b, 501) and while smartphone addiction is seen as similar to internet addiction, little research can be found to investigate the relapse for smartphone addiction. Overall, limited evidence of the sustainability of the behaviour change maintenance has been reported (Kwasnicka et al. 2016, 1–2). Also, it has been suggested that repeated performance of the behaviour can result to a re-evaluation of said behaviour, and the desirability may change (Kwasnicka et al. 2016, 6).

The relapse theory proposed by Kwasnicka et al. (2016, 10) can be seen as a status quo bias, a type of loss aversion (Kahneman, Knetsch & Thaler 1991, 197–199), where the future benefits of new behaviour is constantly evaluated with the present benefits of past behaviour. To counter this effect, and avoid the type 1 system overriding type 2 system with prior behaviour, favourable habitual cue responses and removal of cues that trigger the behaviour have been recommended (Kwasnicka et al. 2016, 10). This way the automatic behaviour adapts to the new status quo, and does not have to maintain willpower and self-regulation against the older behaviour.

According to Michie et al. (2011, 4), the opportunity component provides a context to the decision-making and “makes the behaviour possible or prompt it”. Considering that it is hard to influence to the context in which the smartphone is used, the opportunity component cannot be easily changed with nudges that are compatible with libertarian paternalism. It is therefore recommended that behaviour change is maintained through a longevity of reporting, and by explicating the attainment of decreased smartphone use with positively valenced injunctive emoticon.

2.3 Methods used to research smartphone and Internet use

In this section different research methods and related data analysis methods are presented and analysed. The section also introduces psychoinformatics, a form of collaboration of computer science and psychology, to capture the metadata generated from the real-life usage of the smartphone for statistical analysis. Finally, the section evaluates the impact of self-reporting bias in connection with the research methods, and examines different ways to address it.

2.3.1 Research methods in smartphone addiction studies

Multiple research methods have been used to better understand smartphone addiction. The use of methods has varied depending on the objective of the research, although except for the development of smartphone addiction factors, it is not easy to attribute specific method to a specific objective. By examining different research reports, it can be seen that the experiments have often times included more than one method.

As previously discussed, the factors of smartphone addiction have been examined by using questionnaires only (Kwon et al. 2013b; Körmendi 2015; Lin et al. 2014). The report from Oulasvirta et al. include multiple experiments, each using different research approach. One of them include longitudinal logging of smartphone , another increasing reward value of a quickly accessible application, and the third experiment uses self-reporting of the repetitive use (Oulasvirta et al. 2012, 107–112). Similar to Oulasvirta et al.’s approaches, both Oliver and Lin et al. used an application installed on the test subjects’ smartphones to report usage metrics and related information (Oliver 2010; Lin et al. 2015). Several research reports include a combination of questionnaire and recording the use of smartphone (Lee et al. 2014a; Lin et al. 2015; Montag et al. 2015b).

While the use of self-reporting relatively large research samples including hundreds of participants (Lee et al. 2014b; Gökçearslan et al. 2016), it is considered a less direct measure (Gökçearslan et al. 2016, 647). Researchers suggest self-reporting as a limitation in the research (Lin et al. 2014, 4) . Miller (2012, 233) provides an extensive review of different research methods and suggests that the research methods involving smartphone applications “can do almost everything that the other methods can do and more”.

Perhaps the biggest challenge pertaining to the paper-and-pencil surveys lie in the bias associated with the self-reporting. The self-reporting bias is examined more closely in the next subsection.

2.3.2 Self-reporting bias

It is commonly known that the answers from the respondents to questionnaires are not always representative of the person’s attitudes or personality (Aizen 2005, 14), and that the responses include a common-method variance. This common-method variance can be due to the mental state of the respondent, as well as how socially desirable a reported behaviour is perceived (Markowetz, Błaszkiewicz, Montag, Switala & Schlaepfer 2014, 406; Montag et al. 2014, 159). Some of the bias can also be due to the test subjects’ ability to remember and respond accurately (Montag et al. 2015c, 9). Haug (2015, 304) has characterized this as a recall-bias and time distortion. It has been stated that the criticism towards diagnoses based on patients’ reported experiences has increased in the course of decades, and have resulted to the development of alternative markers and methods for the diagnostic purposes (Lin et al. 2015, 143).

While there are arguments that suggest “to some extent perpetuated misconceptions about common method bias in self-report measures” (Conway & Lance 2010, 325), evidence has been reported that actual behaviour is a better predictor of a phenomenon than a reported variable (Montag et al. 2015a, 435–439). In one report, total smartphone use time obtained from the psychiatrists’ assisted self-reporting was compared with the data generated by the application installed onto the test subjects’ phones. The information from the self-report was significantly lower than the data generated by the smartphone in which the said activity was performed. It was also reported that “as the participants use their smartphone more, the greater is the underestimation.” (Lin et al. 2015, 142.)

By storing information that exactly record the characteristics of the online sessions over the course of time can more accurately report the Internet usage patterns than by using self-reporting (Montag et al. 2015c, 146). Due to this reason, the approach was chosen to this thesis. The purpose was to collect such information for statistical analysis that as accurately as possible capture the real-world events. A special application was developed for this purpose to record those events that occur in the phone, based on which selected research questions could be tested. It has been suggested that this approach “might represent an important step to study human behavior in real life without relying on self-report both in the domains of personality and addiction” (Montag et al. 2014, 159).

However, it should be noted that some literature argue that “self-reports may be the most accurate means of assessing psychological characteristics, given that individuals should have better insight into their own beliefs than would outside observers” (Lee et al. 2014b, 379). As previously discussed, SPAI-SF was selected for this thesis. As no psychiatric professionals were involved in this thesis, the interpretation and use of the results must be performed in such a way that the methods can be applied to healthy test subjects without a diagnosis of Internet or smartphone addiction.

What comes to examining practical approaches to avoid self-reporting bias and to use software-based solutions to store events that reflect the real life view, it is important to examine the respective theoretical frame of reference. This lies in the field of big data analysis in computer science, and its application, psychoinformatics.

2.3.3 Psychoinformatics

Number of research methods have been used to validate smartphone behaviours and addiction. Observation fieldwork has been used to understand how people use phones (Humphreys 2005, 812). Most of the results obtained through the smartphone addiction research, however, are based on self-reported questionnaires. As it was discussed earlier, limited number of research reports document information collection for addiction analysis by way of other means than self-reporting.

It has been argued that the basic methodologies to reliably measure emotion, cognition and behaviour has remained unchanged for decades. Obtaining research data, researchers apply different methods involving observation and self-rated tests. Research methods based on interviews can be costly, are slow to obtain large samples, and typically rely on trained professionals for capturing the data in a statistically reliable format. By applying big data and different computational analytics, different fields of sciences can take advantage of miniaturization of technology, and advanced data processing to create less invasive and more scalable experimental conditions and less biased research results. (Markowetz et al. 2014, 405–406.) This research approach, called psychoinformatics, can be used to synthesize large amounts of information while managing the bias present in the research setting (Yarkoni 2012, 391–395).

A key component in psychoinformatics is known as big data. This term refers to sets of data that are collected through various sources in different formats, and are later processed through various ways of analyses to gain insights of phenomena, business circumstances and human behaviour that were potentially not identified as the data collection took place. These data sets can be very large in size, and can include different types of information from the types of IT systems log files to audio or video. Big data also provides a basis for new types of studies in social science. With the help of big data and computational processing, it is possible to construct experimental conditions that can be better generalized, controlled compared to the real-world situations than by using traditional research methodologies. (Chang, Kauffman & Kwon 2014, 68–69.)

While psychoinformatics is a novel term, number of papers have reported the use of experimental conditions that are compatible with the definition of psychoinformatics. A paper published in 2010 by Verkasalo, López-Nicolás, Molina-Castillo & Bouwman (2010, 243) discuss about "the capabilities offered by smartphones to collect data". This information was transmitted to computers for further processing. Another paper was presented in the same year about a study in which over 17300 Blackberry mobile device users were followed to learn "how users interact with and consume energy on their personal mobile devices" (Oliver 2010).This same research approach have also been applied to investigate the health effects of the mobile phone (Goedhart et al. 2015).

Psychoinformatics have also been applied in the research of smartphone addiction. Results indicated that employing psychoinformatics by way of psych app can be an effective way in treating smartphone addiction (Lee et al. 2014a, 9). In another research, diagnostic criteria to identify smartphone addiction was validated with a psych app. The data generated by the application was compared with the data provided from the psychiatric interview. Smartphone addiction was shown to significantly associate with the smartphone usage frequency, and that the trend in median smartphone usage time is more significant measure of identifying tolerance-related symptoms of smartphone addiction than the total duration of smartphone use per day. (Lin et al. 2015, 143–144.)

While traditional self-reporting results can provide useful information, such as average time spent each day for different communication methods (Ehrenberg, Juckes, White & Walsh 2008, 740), the use of psychoinformatics can provide insights to a far richer degree. Oliver reported in the paper about the duration and closeness of the interactions, stating that "approximately 80% of device interactions are less than 90 seconds in length, and that 50% of interactions occur within 115 seconds of each other" (Oliver 2010, 1). It would be hard to justify the validity of the before mentioned insights if it was generated from the data generated through self-reporting measure.

Number of smartphone applications has been developed to inform users of their smartphone use behaviour. Some of these applications have originally been developed for research purposes, such as Menthal (Montag et al. 2015a, 437) and Offtime Research and Surveys (Menthal 2016; Offtime 2016), and have later evolved as distinct applications with a utility value to the smartphone users. Common to most of the applications involving smartphone addiction lies in that they report the usage times and opening times of the phone in rich details, and include functionality to remind a smartphone user if the approach or reach the self-specified time limit. Some of these applications also provided a mean of locking a phone should the target time be reached. (Lu 2016; Pumpic 2016; JK.Fantasy 2016; ZeroDesktop Inc. 2016; RinaSoft 2016.)

One application also includes a personality assessment and reporting (Menthal 2016), though it remains unclear for what purpose this information was used. While these readily available applications might provide excellent insights into the people's smartphone behaviours, not one of these applications were identified suitable for this thesis. None of the available applications were found to include functionality that had relied on active reflection of the smartphone use and use of nudges. The applications did not either report the use of positive reward or activating a goal-directed behaviour to provide a positive reward of a compliant behaviour to a smartphone user.

Due to this thesis focusing on the behaviour, it was justified to present interventions constructed according to different type of nudges, and measure the impact of these interventions in a course of time. Due to the method of this study, a mobile application was developed to conduct the study and present users with the experiments. The causes for requiring ability to inflict active reflection and goal-directed behaviour is discussed in the below section.

2.3.4 Analysing the big data for the basis of results

Often times the methods used in statistical and inferential analysis makes certain assumptions towards the research data. In the case of correlation and linear regression, these assumptions include that the research data is normally distributed, is linear, and is stationary. In order to use the inferential methods including correlation and linear regression, the reliability of the results is associated with how much the research data conforms to these assumptions. (Hanneman, Kposowa & Riddle 2012, 435–436, 463.)

Normally distributed research data means that the mean, median and mode all change at the same time in the both sides of the midpoint, resulting to a bell curve (Hanneman et al. 2012, 152–166). Linearity of the data means that any unit change in one variable changes the other variable always at the same amount (Hanneman et al. 2012, 436). Stationary data means that if the research data is sampled in the time dimension, the time span that the sample represents has a diminishing effect on the results of the data, i.e. the results are not dependent on time span during which the research data was collected (Kocenda & Černý 2014, 17). Specifically, to the regression analysis, the data should conform to the homoscedastic expectations, i.e. the dispersion of the results in Y axis are independent on the location of the data in X axis. It has been shown that some research data in social sciences does not fulfil to this assumption. (Hanneman et al. 2012, 435–436.)

The purpose of data analysis in research is to identify necessary parameters to construct the model of the phenomenon, and to confirm that the constructed model represents the phenomenon under observation (Huang et al. 1998, 904). It has been suggested that the data analysed in social sciences do not always conform to the assumptions for linearity, stationarity and normal distribution (Hanneman et al. 2012, 176). At times the research data needs to be transformed or pre-processed to make research data distribution more normal (Hanneman et al. 2012, 436). However, in many cases the underlying system, either natural or man-made, produces data that has nonlinear or nonstationary characteristics (Huang 2005, 1). In these cases, the data analysis methods suitable for nonlinear and nonstationary data should be used to achieve reliable results.

One of the methods suitable for nonlinear and nonstationary data analysis is Hilbert-Huang Transform (HHT). HHT has been shown to be a superior tool to analyse data in time-frequency format that has nonlinear or nonstationary characteristics (Huang 2005, 14), and has been used in analysing data generated by seemingly stochastic processes, such as heart-rate variability (Yeh, Sun, Shieh & Huang 2010), surface temperature of earth (Huang et al. 2009), financial metrics (Huang, Wu, Qu, Long & Shen 2003) and to separate waves induced by tsunami from tidal waves (Huang et al. 1998, 971). The basis of the method lies in that HHT decomposes the research data into intrinsic components (IMFs), each with a distinct oscillatory mode that is “physically meaningful”, i.e. representing an underlying real-world phenomenon (Huang 2005, 5, 10–12). As the HHT is adaptive, accommodating to the local variations of the data, it is applicable for non-linear and nonstationary data, and has been shown to represent the underlying physical world phenomenon in addition of mathematically fitting the data (Huang et al. 1998, 904, 910–911).

As part of the process, the residue from the process represents the overall trend of the data (Huang 2005, 10). Depending on the real-world phenomenon under observation, the trend can be discarded, or it can become of interest and importance of the research. Examples of these phenomena include climatic data analyses (Wu, Huang, Long & Peng 2007, 14889).

The decomposition process of Hilbert-Huang Transform has been subsequently improved by "averaging the modes obtained by EMD applied to several realizations of Gaussian white noise added to the original signal" (Torres, Colominas, Schlotthauer & Flandrin 2011, 4144), and is called Ensemble Empirical Mode Decomposition (EEMD). As this change has substantially improved HHT as a method (Wu & Huang 2009, 25), EEMD was also used in this thesis.

One previous research report has provided evidence that the data collected from the smartphone research can be analysed using HHT (Lin et al. 2015). In this thesis, the relationship between the results from smartphone addiction questionnaire and the psychoinformatics data was examined, and the decomposition of the research data provided three IMFs with a residual that represented the overall trend of the data. (Lin et al. 2015, 139–141.) The results indicated significant association between smartphone addiction and the trend (Lin et al. 2015, 143). Hsieh, Hsiao, Ji and Yip (2013) have also used HHT to analyse emotional reactions of people with internet addiction.

While HHT has proven to be a reliable method for analysing the research data in time dimension, it may still be necessary to use additional inferential methods for the additional results. It is common to test the hypotheses in social sciences with two-sample tests in order to discover differences between the treatment group and the control group, or to compare outcomes of two treatment programs. In research reports investigating the difference in behaviour pertaining to household energy consumption, as well as analysing the anxiety resulting from a withdrawal of a phone, Analysis of variance (ANOVA) has been used (Lepp et al. 2014, 293–294; Abrahamse et al. 2007, 271). In the context of smartphone addiction research, where association between self-reported information and the information collected by the smartphone application has been investigated, paired t-test and Pearson correlation has been used (Lin et al. 2015, 141). Both of these tests assume homoscedastic research data, that is, "the variance of the variable of interest is the same across the population groups" (Hanneman et al. 2012, 340).

Extensive evidence from prior research reports suggests that the introduced methods, that is, HHT, paired t-test and ANOVA, act as a sufficient basis for reporting inferentially reliable results from the smartphone addiction and usage research. Due to this evidence it was decided that these methods are employed in the data analysis. However, it has been previously reported that the sample size and homogeneity of the sample, as well as limited time span of the research can influence to the detection of trends in some of the parameters generated by the smartphone application (Lin et al. 2015, 144). These limitations should be contemplated with the results of the results.

3 Research design and methods

This chapter describes the research design and the methods. The first section introduces and illustrates the overall research design, including relevant screenshots of the psych app used in this thesis. The second section describes the stages of the study, including the smartphone addiction inventory questionnaire included in the application, as well as the nudges with their illustrations on the phone. The third section explains data collection in detail including sampling (recruitment) of the test subject, pre-processing of the data. Finally, the fourth chapter explains the data analysis, inclusive of the pre-processing, sampling of the test subjects for the basis of further research, the methods used to analyse the questionnaire data, as well as the methods used to analyse the big data generated by the psych app.

The purpose of the thesis was to explore the effect of different type of nudges to smartphone use. While previous studies have focused on validating the diagnostic criteria, or exploring different smartphone usage indicators, it is hard to find a study that had focused on healthy test subjects, and to lower the smartphone use regardless of whether the usage has been diagnosed or identified as problematic.

This thesis focused on the following questions:

1. How does the SPAI-SF associate with the smartphone usage of healthy users?
2. How do healthy smartphone users respond to different types of nudges depending on whether the nudge focuses on capability, motivation or goal-attainment?
3. How does the effect of nudges differ between the groups?
4. How does smartphone usage relapses to the previous behaviours once the nudges are not present?

In order to answer to these research questions, the study included a self-assessment measuring smartphone-related behaviours, as well as a set of interventions carried out by a psych app installed to the test subjects' smartphones. Over the course of five weeks, the screen unlocking and locking events of test subjects' smartphones was tracked. During the second, third and fourth week, nudges were performed at every screen unlock event to nudge test subjects in a specific way. The capability-nudge presented key indicator values. Both the motivational-nudge and goal-attainment-nudge presented key indicator values and valentic emoticon. In the second nudge the emoticon indicated the attainment of the lower level of use compared to the previous week. In the third nudge the emoticon signified the attainment of the self-defined goal. The psych app executed the nudges according to the research design, and uploaded data to the cloud computing infrastructure. The collected information was processed into daily values of key indicators (presented further down) per user, and analysed with the results from SPAI-SF to examine the impact of nudges to the phone usage behaviour.

3.1 Research design

The study was initiated by a test subject by installing the application onto the smartphone. The application was freely available in Google Play store, and was compatible with smartphones with Android API16 and above. This included approximately 10000 different device types and potentially millions of users. The users were presented information about the research prior to their installation of the application, and the research information sheet was made available to them in the application.

As the application was only available in Finnish and English, it can be expected that the application did not gain much interest in countries with low Finnish or English literacy. Also, due to the high amount of applications available in Google Play application stare, the target segment was expected to be those individuals who have an interest towards the topic and had learned about the application and the study first through social media or from friends and family. Due to these reasons the typical test subject is expected to be a university student or an employee in the early stage of their career from Southern Finland, or someone from within the social circles of the test subjects.

The actual study was constructed for consecutive five stages, each of them lasting for 7 days, and therefore the total duration of the study was five weeks. As soon as the users started the application for the first time, the study initiated. The application registered itself to the service hosted in Google cloud computing infrastructure. Users could respond to the self-assessment questionnaire at their convenience during the study, and the time of response or abstaining from the questionnaire did not have influence to the progress of the study. Figure 1 below, illustrates the progress of the study, including the views in the actual application, as well as the type of nudge in the screen.

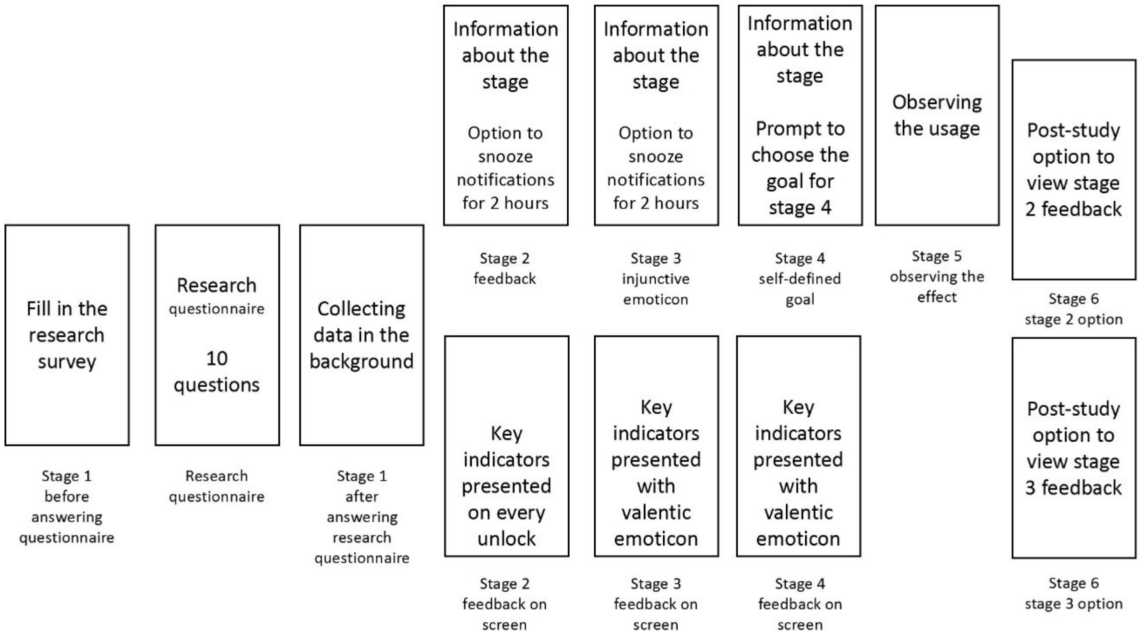


Figure 1: Stages of study

The smartphones uploaded the data in near-real time to the Firebase cloud services provided by Google Inc., and the data analysis was developed and performed partly during the study. The final results were processed once the sample of the test subjects had completed the full 5 weeks of the study. Once the study had elapsed for 5 weeks, the test subjects had a choice to continue to use the application, or uninstall the application from their smartphone. The data collection continued as long as the application was installed in the phone.

The data was extracted as a JSON file, and after the pre-processing, imported to MATLAB to perform Hilbert-Huang Transform (HHT) and consequent processing of the data, and finally to SPSS to perform descriptive inferential analysis of both the questionnaire data and the data generated from the big data.

An important step in data analysis was the definition of the key indicators for smartphone usage. These indicators are quantifiable metrics that were calculated from the big data, summarizing the smartphone usage in ways that could be followed throughout the study.

Some studies were found to report results similar to the key indicators used in this thesis. A paper from Oulasvirta et al. (2012, 108–109) report three studies, one of which includes median duration of smartphone usage per day, 160 minutes per day per user (pdpu). This thesis also includes the median number of phone usage sessions and short, instantaneous, reward-based sessions (SIRBS) per day, 34.11 pdpu and 3.19 pdpu, respectively. Lin et al. (2015) have used similar data collection technique, and report phone usage both in daily frequency 73.1 ±

43.8 times, as well as daily use time (duration) 4.20 ± 2.06 hours. However, the report does not include Median SOT or median SFT values, even though the researchers mention that the median session time was calculated for inferential statistical analysis.

Oliver (2010) has presented mean daily activity time and daily session counts as the indicators of phone activity. Lin et al. (2015, 140) and Oulasvirta et al. (2012, 109) have earlier used median duration of the events, and it has been reported to better fit to the normal distribution than using mean duration. Finally, Oulasvirta et al. (2012, 108) have suggested SIRB (Short duration, Isolated, Reward-Based) sessions as a proxy for habitual device usage. As the application used in this thesis did not include information regarding the smartphone applications in use, the reward-based component was not included into the definition of Glances.

Based on previous research reports, a set of key indicators were developed for this study, described in Table 1 below.

Key indicator	**Description**
Unlocks	Number of phone usage sessions
SOT	Screen on time (seconds per day)
Median SOT	Median Screen On Time of each session (seconds)
Glances	Number of phone usage sessions equal or shorter than 30 seconds in duration, over 10 minutes apart from the previous session.
Median SFT	Median Screen Off Time between two sessions (seconds)

Table 1: Key indicators used in the research

The data was pre-processed and tested to identify levels and changes in these key indicators, each of which were assumed to correspond with one or more SPAI factor. Figure 2 below, featured in Appendix 5 in an enlarged format, illustrates the stages in data collection and analysis.

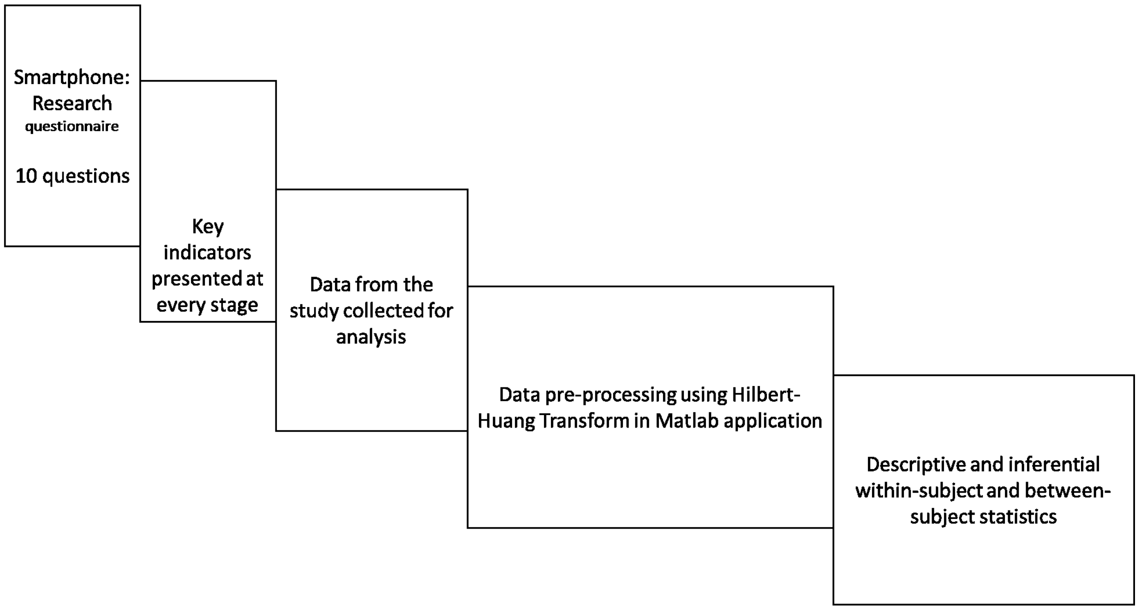


Figure 2: Study progress

The first phase of the study was to collect the responses to SPAI-SF and observe the smartphone usage to determine the baseline of the usage for a test subject. The second phase was to record the smartphone usage and perform the nudges during the three weeks. The third phase of the study was to observe the smartphone usage without interventions to observe possible relapse in smartphone usage. The information collected from the study was transferred from Google cloud infrastructure, converted to be processable in MatLab, and the resulting information was finally tested for inferential statistics in SPSS.

3.2 Stages of study

This section introduces the five stages of the study, explains the nudges and presents the user experience seen by the test subjects. The section first introduces the self-assessment presented to the test subjects, followed by the description and illustration of each stage during the study.

3.2.1 Self-assessment

A short form of Smartphone Addiction Inventory questionnaire was used in this thesis. As soon as the test subject invoked the application, they were prompted to take the self-assessment survey as illustrated in Figure 3 below. Test subjects could voluntarily respond to the questionnaire, and the responses were collected to the cloud. Appendix 1 presents the list of questions in the self-assessment. The questionnaire measures four smartphone addiction types as defined by Lin et al. (2014).

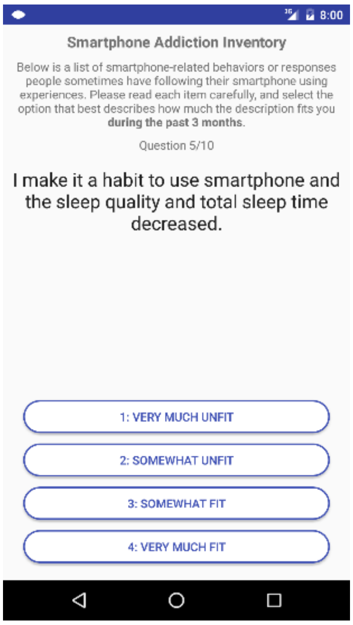


Figure 3: Question in the SPAI-SF

Self-assessment was based on a Smartphone Addiction Inventory (Lin et al. 2014). The authoring research team provided a short form of this questionnaire, consisting of 10 questions of the 26 questions present in the full-length SPAI scale. The questionnaire was available in English, as well as translated to Finnish. The test subjects were prompted to take the questionnaire, but they were not forced to do so. The questionnaire included 10 questions, and they were responded by pressing the button stating the level of agreement or disagreement with the statement regarding the smartphone behaviour or reaction. The responses were measured on a 4-step Likert scale, “1” indicating the statement to very much unfit, “2” to somewhat unfit, “3” to somewhat fit and “4” to very much fit.

3.2.2 Nudges in different stages of the study

In the first week, the Baseline stage, the smartphone application operated in the background, and did not have any controls or interventions for the user. The application screen indicated the number of days left to the next stage, in the interest of demonstrating the progress of the study, and keeping people anticipating the next stage (Figure 4). The baseline stage of the study did not include a nudge, but the purpose of this stage was to create a personal baseline of smartphone usage.

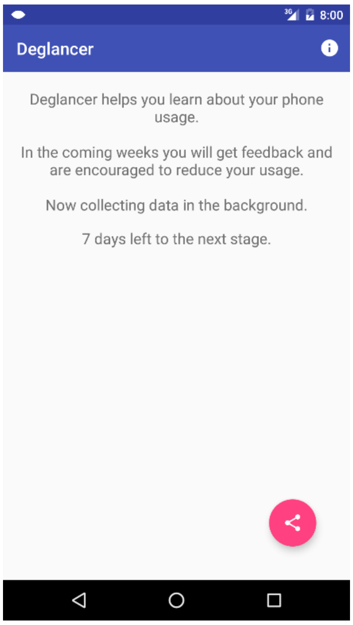


Figure 4: Application in the Baseline stage

In the second week, Capability stage, as soon as the user unlocked the screen, the application presented three key indicators: number of minutes that the phone was locked before this unlock event, the number of unlock events so far during the ongoing day, and the total duration that the screen has been turned on during the ongoing day (Figure 5). The purpose of this stage was to test the effect of information to the smartphone use. The nudge was designed to be compatible with Hansen & Jespersen's (2013, 21) definition of Transparent type 1 nudge. In this category, the reflective thinking of a subject is a by-product of the nudge.

In all stages where notifications were presented to the user, user had an option to snooze notifications for 2 hours at the time. This was recorded to the data as an event that could be explored for frequency and occurrences, but the data was not available, and it was not used, for inferential analysis.

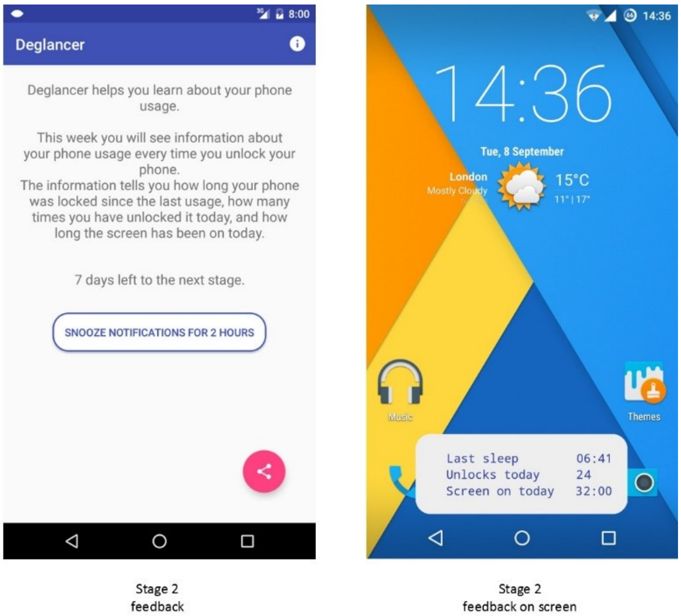


Figure 5: Application screen and notification in the Capability stage

In the third week of the study, Motivational stage, a user was presented with a similar notification upon every unlock of the smartphone than what was presented in the second stage. The only difference was that each of the smartphone usage indicators were preceded with a positively valenced injunctive emoticon if the cumulative use on a current day up to the current hour was less than the same day one week earlier (Figure 6). E.g. if the last sleep of the smartphone was longer than the average sleep time in the Capability stage, if the number of unlocks up to the current hour of the day was less than the number of unlocks up to the current hour one week earlier, and if the total screen time up to the current hour of the day was less than up to the same hour of the day one week earlier, one or more of the three indicators were preceded with an emoticon signifying a thumb pointing up. The purpose of this stage was to test the effect of positively valenced injunctive emoticon based on an external party's judgment.

The nudge in Motivational stage was designed to build on the motivational component of the COM-B model. As the positively valenced injunctive emoticon was indicating an attainment of a desired behaviour, it was intended to reinforce commitment to strive for lower smartphone use. The nudge also built on Hansen & Jespersen's (2013, 23–24) definition of Transparent type 2 nudge. In this type, the nudge makes an attempt to influence behaviour through reflective thinking. The emoticon (or the absence of it thereof) was provided feedback to reinforce the commitment mechanism, but the test subject maintained a complete freedom of choice, both before they decided to engage with the phone in the first place, and after they had decided to open the phone and became subject to the nudge.

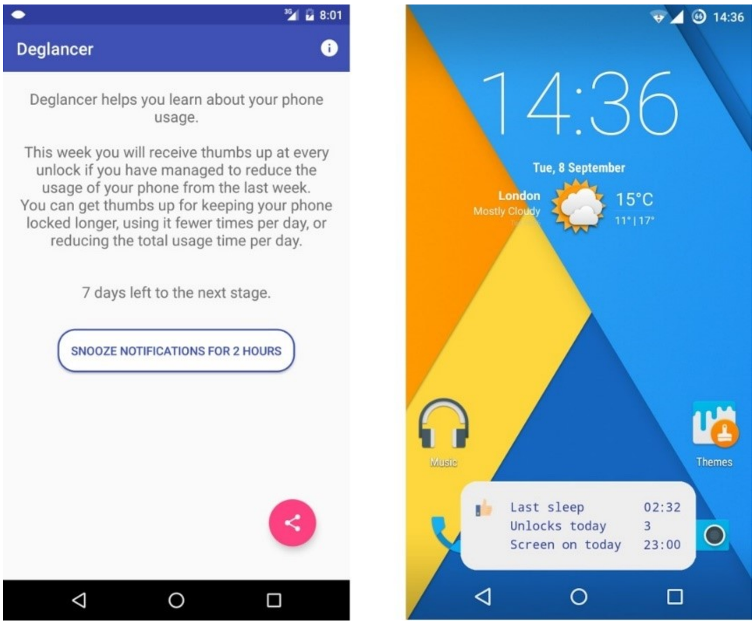
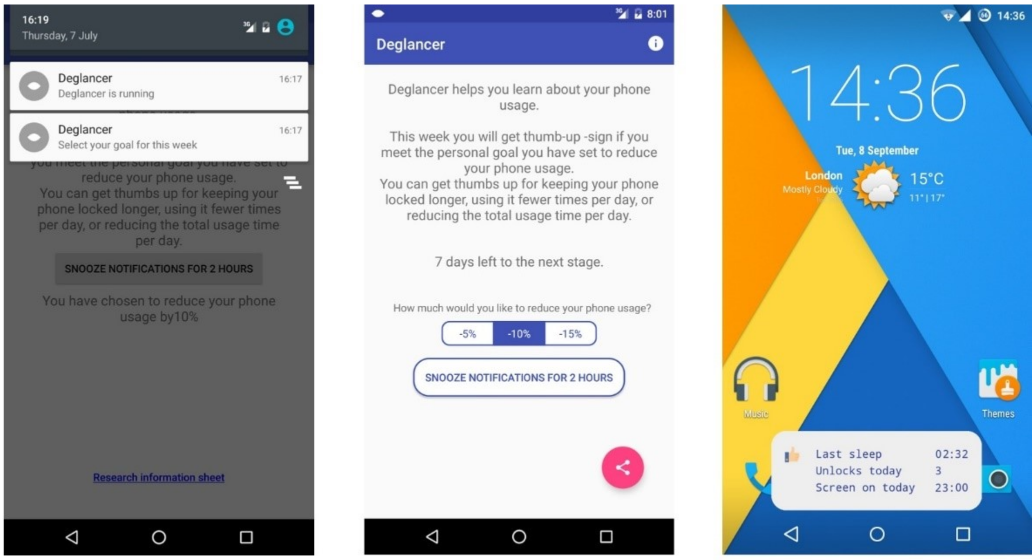


Figure 6: Application screen and notification with injunctive emoticon

After the Motivational stage, the study moved to the fourth week, Goal-attainment stage. User was notified with an Android notification to select a goal for how much he or she wishes to decrease the phone usage this week. If the user did not select a goal, the application used the default goal of 5 % improvement to the previous week. Every time the user unlocked the phone, the application calculated if one or more of the indicators had improved more than the target percentage compared to the previous week's information. That is, if the sleep time was at least 5 % longer than the average sleep time in the previous week, if the number of unlocks was at least 5 % less than the number of unlocks up to the same hour of the day in the previous week, and if the total duration of the screen time had been at least 5 % less than up to the current hour of the day in the previous week. If these conditions were true for any indicator, the indicator was preceded with the same injunctive emoticon than what was used in the Motivational stage (Figure 7). The purpose of this stage was to test the effect of goal-attainment, and the effect of injunctive emoticon based on a personally set goal.

As in the Motivational stage, the nudge in the Goal-attainment stage built on the motivation component of the COM-B. However, as the stage included a task to define the percentage of the desired reduction in smartphone use, the goal-setting intended to direct attention and effort to reach the goal defined by the test subject. In order for the test subjects to more easily maintain their state of goal attainment, the test subjects would have to reflect their phone usage before engaging with the phone, thus reducing the number of phone unlocks.

The nudge in the Goal-attainment stage too was designed to be compatible with Hansen & Jespersen's Transparent type 2 nudge. By prompting the test subject with active decision-making regarding the amount to reduce their smartphone use, it was expected that the test subjects would make effort to attain the goal that they have specified.



Stage 4
Notification to select a goal

Stage 4
Application screen to select a goal

Stage 4
Notification at screen unlock

Figure 7: Android Notification, application screen and notification in the Goal-attainment stage

In accordance to the theoretical framework, the injunctive emoticon in the Motivational stage or the Goal-attainment stage was positively valenced or absent.

As the study progressed to the fifth week, all notifications stopped, and application only recorded the user behaviour for one week. In the same way with the first stage of the study, the fifth stage did not involve a nudge. The purpose of this stage was to investigate if users relapse to their prior behaviour after the nudges are not present.

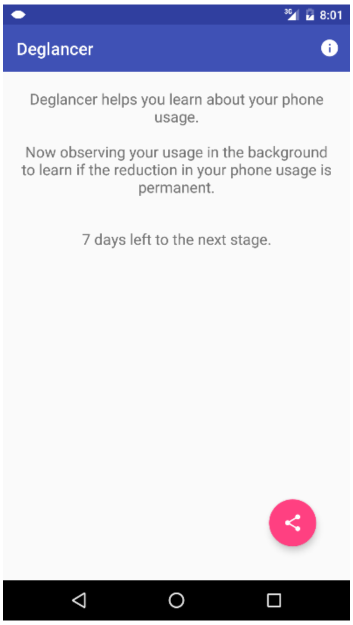


Figure 8: Application screen in the Observation stage

The application notified user that the study had completed after full five weeks of the study had elapsed. The user could still continue to use the application, and the user could choose the type of message to present at every unlock. The application continued to collect the data as noted in the research information sheet.

3.3 Smartphone usage data collection

The smartphone application was running as a background process in the smartphone for the whole duration of the experiment. Every time the application unlocked or locked the screen, the application stored the time stamp of the event to the database. The data generated by the application was uploaded to Google cloud infrastructure in a near-real-time fashion. The smartphone users did not have access to the information generated by the application. The described implementation was compatible with the previous research by Lin et al. (2015, 140).

Due to the technical requirements, the application presented a small icon in the status bar of the application. It was unclear how much the presence of this icon invoked self-recognition and control during the study. Also, it can be expected that there is a degree of willingness to conform to socially desired behaviour by installing the application and participating in the study. However, it can be assumed that as the application did not interact with the smartphone user in the first week of the study, at least part of the self-regulation towards conforming with the expectedly desired behaviour was diminishing.

3.4 Data analysis

Table 2 below summarizes the steps in data analysis with description, purpose and the tools used for each step. Part of these tools were developed during the project, and part of the tools were adopted from the earlier research projects.

Phase	Description	Purpose	Tool
Convert data from cloud to a format compatible with Matlab	Extract data set in JSON file format from Google Cloud, extract individual user data and responses to SPAI-SF responses, and transpose all data to CSV files	Process information in a file format that could be more easily manipulated in Excel, SPSS and Matlab.	Unix shell scripts written for this purpose
Remove outliers	Process test data according to the pre-processing specification and remove test data that does not conform to the expectations	Remove outliers that are due to the expected technical problems in the study, or perceived inadherence or purposeful manipulation of the test data	Unix shell scripts written for this purpose
Calculate SPAI-SF factor scoring based on responses	Calculate scoring from the SPAI-SF responses and normalise scoring range.	Normalise SPAI-SF factor scores to scale 0-10 for each of the factor for more intuitive comparison.	Excel chart using factor loadings from the original SPAI research (Lin et al. 2014)
Group test subjects	Group test subjects using TwoStep cluster analysis based on SPAI-SF factors to group Low and group High, illustrating their relative SPAI-SF score.	Group individual test subjects based on the SPAI-SF factor scoring based on their responses.	TwoStep clustering method in SPSS v23
Calculate key indicators	Process screen events and calculate key usage indicators for each test subject	Process raw event data and calculate key indicators	Unix shell scripts written for this purpose
Execute HHT/EEMD smoothing	Process calculated key indicator data for each user using Hilbert-Huang Transform and	Extract trend of changes in each key indicator	Matlab script with HHT/EEMD package

	Ensemble Empirical Mode Decomposition		
Calculate inferential statistics	Test extracted trend data with General Linear Model and t-test by group by stage	Test extracted trend data for statistical inferences	SPSS v23

Table 2: Description of data analysis stages

3.4.1 Pre-processing the data

Due to the recruitment protocol, the test subjects were able to install the application and join the study at their convenience. Because of this reason, the exact start time during the day could not be controlled, and there was a possibility that the first day of study did not account for all of the phone usage during that day. In order to maintain the consistency of the data between different stages, the data of the first day of each five stages was discarded for all, including only the days 2 — 7 from each stage of the study. Table 3 below illustrates the filtering of the data for the analysis.

Stage	Day number discarded	Day numbers included	Newly computed day numbers
Baseline	1	2,3,4,5,6,7	1,2,3,4,5,6
Capability	8	9,10,11,12,13,14	7,8,9,10,11,12
Motivational	15	16,17,18,19,20,21	13,14,15,16,17,18
Goal-attainment	22	23,24,25,26,27,28	19,20,21,22,23,24
Observation	29	30,31,32,33,34,35	25,26,27,28,29,30

Table 3: Days included in the research

As the first day of the study was at the discretion of the test subject, and as the data was converted to the sequential number of days starting from the beginning of the installation, any events in the real world that can be expected to systematically influence to the data on a given date were scattered to different day numbers. These events include for example summer holiday periods, weekends and Olympic games, all coinciding with the period of this thesis.

3.4.2 Recruiting participants and selecting the data to the study

The test subjects were recruited via social media (Twitter, Facebook, LinkedIn), and through the social circles of the test subjects and the thesis worker. Test subjects participated to the study by installing the application used in the study.

After the data collection, the data was filtered so that those test subjects that completed the full five weeks of studies was selected for further investigation. This approach was similar to those of earlier research practices by Montag et al. (2015b, 3). Users with more than three consecutive days missing from the data was excluded from the analysis, indicating termination of the study. Data from users that did not complete SPAI-SF was excluded from the between-subjects tests.

3.4.3 Analysing responses to SPAI-SF

The results of the SPAI-SF were extracted and processed separately in SPSS. Firstly, the questionnaire answers from with the test subjects were extracted from cloud infrastructure to Microsoft Excel. Then, each SPAI-SF question was given a loading in each four factors: Compulsive use, Tolerance, Functional Impairment and Withdrawal. Finally, total score for each factor was calculated using responses and their associated factor loadings as presented by Lin et al. (2014, 3). The factor loadings are listed in Appendix 2.

Due to the original SPAI questionnaire using all of the 27 questions, as opposed to the 10 questions present in the SPAI-SF, the factor scores are not comparable to those scores presented in the reference report by Lin et al. (2014). To present factor scores from SPAI-SF for more intuitive interpretation, the factor scores were normalised to scale 0 — 10, resulting to a total score of 0 — 40 for SPAI-SF.

Heijden, Klein, Müller and Potters (2011, 3) have earlier shown that the effects of nudges are not specific to the economic or sociodemographic background variables. Altmann and Traxler (2014, 11) have also reported that the background variables does not significantly correlate with the effects of treatments. On the other hand, Tossell et al. (2015, 38) have explored smartphone addiction between addicts and non-addicts, grouped based on the results of the smartphone addiction measurement instrument. In order to investigate the effects of nudges based on SPAI-SF, the test subjects were grouped based on their normalised factor scores. The objective was to forms groups of users that responses were similar to their peers within each group. Two Step cluster analysis was used in SPSS using four SPAI-SF factor scores as continuous variables. Number of groups was determined automatically by SPSS. These groups were used later in between-subject tests to examine if there were significant differences in smartphone usage between the groups.

3.4.4 Measuring the smartphone usage indicators

The raw data included time stamps of events when the phone screen was unlocked (SCREEN_ON) and locked (SCREEN_OFF). These raw events were processed with scripts developed for this purpose, and the key indicators presented in Table 1 was extracted for each user, stage and day of study. The data was transferred to MatLab program, and the time series of each key indicator was processed with Hilbert-Huang Transform (HHT). In this so-called sifting process, the time series of each key indicator were broken into intrinsic mode functions (i.e. IMFs), and by sequentially decomposing these intrinsic modes from the original signal, the remaining data represented the trend of the data over the study period. This analysis was compatible with the method used by Lin et al. (2015, 140–141). Further to the processing of the data in Matlab, the results were transferred to SPSS for descriptive and inferential analysis.

Inferential statistics was performed as within-subject t-test, measuring the effect of nudges in Capabalibity, Motivational and Goal-attainment stages compared to the Baseline and to the Observation stage. Between-subject tests were performed using one-way ANOVA to identify differences in the five key indicators of the smartphone usage between groups. Finally, the effects of nudges between the stages of the study and between the test subjects grouped using SPAI score were performed by using GLM Univariate.

4 Results

This chapter presents the results of the thesis. The first section reports the overall participation statistics and describes the process of selecting the test subjects for the analysis. The second section presents the Smartphone Addiction Inventory Short Form (SPAI-SF) results, followed by the validity and reliability analysis of the SPAI-SF. Finally, the fourth section presents results derived from the information generated by the psych app. This section includes descriptive statistics, within-subject inferential statistics, between-subjects inferential statistics without accounting for the progress of the study, and between-subjects inferential statistics accounting for the progress of the study and the different nudges in different stages of the study.

4.1 Selecting test subjects for descriptive and inferential analysis

Total of 201 users installed the application. 30 users never used the application, and one users responded to the SPAI-SF without transmitting any smartphone usage information to the cloud. The information collected from the SPAI-SF was used in the cluster analysis, as the activity was independent of the data collected by the application. The sociodemographic background variables of the users were not collected as they were not in the scope of this thesis.

170 users used the application to an extent that the application transmitted usage information to the information storage in the cloud. Of these users, 79 users stopped the study before having completed all the 35 days of the study, and 91 users completed the study until the last day.

Of the 91 users that completed the study, data from 13 users had to be discarded due to them being devices of the thesis worker or for technical reasons. The technical reasons were abnormally high SOT - suggesting that an application installed onto the phone reported phone standby time as usage times, or that the collected data was corrupted.

As a result, the data analysis was performed for the remaining 78 users. One of these users did not respond to the SPAI-SF, and the data from this user was only used in descriptive analysis and within-subject inferential analysis. The data collected from the remaining 77 users were used in between-subject analysis.

In total of 606052 events, each of them signifying either the opening or closing of the smartphone screen. When one day of one user was measured as a unique sample, the data was collected over 2276 unique usage days, representing approximately 7344 hours' worth of smartphone usage.

4.2 SPAI-SF responses

The highest mean score was reported from compulsive behaviour, and the lowest mean score was reported from tolerance. The descriptive statistics are presented in Table 4 below.

SPAI-SF Factor	Mean	SD	Min	Max	N
Compulsive behaviour	4,245	1,647	0,510	9,661	171
Functional impairment	3,892	1,393	1,123	8,642	
Withdrawal	4,015	1,777	0,617	9,044	
Tolerance	3,831	1,998	0,268	9,227	
Total	15,984	5,326	5,090	28,797	

Table 4: Descriptive statistics of the factors from SPAI-SF

In order to review the nature of factors with the factors presented in the earlier research reports, paired t-test between each two factors were performed to determine the significance of the mean difference among the 171 participants. The differences were highly significant in p < .001 between all other pairs except Withdrawal and Tolerance. Table below illustrates the differences in more details.

From SPAI-SF Factor	To SPAI-SF factor	Significance of mean difference
Compulsive behaviour	Functional impairment	$t(170) = 24.647, p < .001$
Compulsive behaviour	Withdrawal	$t(170) = 10.206, p < .001$
Compulsive behaviour	Tolerance	$t(170) = 9.474, p < .001$
Functional impairment	Withdrawal	$t(170) = -15.334, p < .001$
Functional Impairment	Tolerance	$t(170) = -20.122, p < .001$

Table 5: Significance of mean differences between factors

The 171 test subjects were grouped using Two Step clustering in SPSS, and the clustering reported 2 groups, named as group Low and group High. Two Step cluster analysis is an algorithm employed by the SPSS statistical analysis software to explore to identify groupings in a dataset. The SPAI-SF factor scores were used as continuous variables, and the number of groups were determined automatically by the Two Step cluster analysis. The differences between the groups are presented in Table 6 below.

			Compulsive behaviour		Functional impairment		Withdrawal		Tolerance	
		N	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Group	High	80	5,25	1,26	4,84	1,20	5,18	1,40	5,30	1,41
	Low	91	3,36	1,42	3,06	,94	2,99	1,41	2,54	1,48
	Combined	171	4,25	1,65	3,89	1,39	4,02	1,78	3,83	2,00

Table 6: Descriptive statistics of SPAI-SF factor scores between subjects

The four SPAI-SF factors are formed using factor loads for each of the 10 questions as per Lin et al. (2015). The descriptive statistics of SPAI-SF questions are presented in the Table 7 below.

Question	Group	N	Mean	SD
Negative interpersonal	Low	91	2,38	,952
	High	80	2,69	,648
Use longer and more money	Low	91	1,63	,661
	High	80	2,35	,858
Try to spend less time	Low	91	1,80	,734
	High	80	2,73	,763
Aches and soreness	Low	91	1,32	,594
	High	80	2,36	,860
Sleep quality and time decrease	Low	91	1,48	,621
	High	80	2,68	,759
Neg. eff on school and work	Low	91	1,34	,542
	High	80	2,28	,763
Restless and irritable when unavailable	Low	91	1,81	,829
	High	80	2,59	,837
Uneasy once I stop using smartphone	Low	91	1,64	,691
	High	80	2,51	,746
Hooking longer	Low	91	1,87	,703
	High	80	2,89	,595
Subst. increased amount of time	Low	91	1,54	,638
	High	80	2,40	,805

Table 7: Descriptive statistics of SPAI-SF responses between groups

This thesis was the first using SPAI-SF in a shortened form with 10 questions, developed from the full-length SPAI with 27 questions. The validity of the questionnaire was examined by performing a Pearson Product Moment to test if the responses to the individual questions were statistically significantly correlated with the total score computed as a sum of all responses to the questionnaire (Greene & D'oliveira 2005, 152–160).

Apart from the first question, "Although using smartphone has brought negative effects on my interpersonal relationships, the amount of time spent on Internet remains unreduced", all questions had a Pearson correlation at least or higher than .584, significant at the $p < 0.01$ level. The Pearson correlation of the first question of the questionnaire was .380, significant at the $p < 0.01$ level.

The purpose of this reliability testing was to confirm that the questions are internally consistent, and that the questionnaire measures the results consistently (Tavakol & Dennick 2011, 53). Lin et al. (2014, 2) have tested the original SPAI questionnaire for its reliability during its development, and Cronbach's alpha for the total scale has been reported to 0,94. In this thesis, a short form of the questionnaire was used, and therefore questionnaire was first tested for reliability. Cronbach's alpha for the SPAI-SF in this study was 0,818. If the first question, "Although using smartphone has brought negative effects on my interpersonal relation-ships, the amount of time spent on Internet remains unreduced", had been removed from the questionnaire, the reliability of the data would have improved to 0,829.

Both validity and reliability tests suggested that the first question should have been excluded from the study, however as this question was reported to have a high factor load for measuring compulsive use, and as the reliability of the original SPAI questionnaire was reported high including the first question, the question was included to the study. The validity and reliability test results, as well as questionnaire descriptive statistics are illustrated in richer details in Appendix 3.

4.3 Smartphone usage

This subsection presents the results collected by the psych app. Firstly, the descriptive statistics from the smartphone use are presented. Secondly, results from within-subject inferential statistical tests are reported to indicate how phone usage differed as the study progressed between stages. Thirdly, between-subject inferential statistical tests were conducted to examine differences in the usage patterns between groups. Finally, between-subject tests were executed between stages to identify how responses to different nudges differed between groups as the study progressed between the stages.

Within-subject and between-subject tests were measured based on the key indicators of the phone usage: unlocks, SOT, Median SOT, Number of glances, and Median SFT. The last between-subject tests were measured based on the same key indicators, and the results were compared between the stages of the study. The F-test was used to test the significance between the progress of the study.

The descriptive statistics are presented based on the dataset before pre-processing using Hilbert-Huang Transform (HHT). However, due to the HHT being used in pre-processing stage to address the non-linearity and non-stationarity of the data, the comparison of the key indicator values using original units of measure might not be accurately depicted. This is especially true with Median SFT where HHT has smoothed the data to a negative range without equivalent real world phenomenon.

4.3.1 Descriptive statistics

Total of 2304 observations collected over the 5-week study period were tested. Each observation was one day of one test subject, equivalent to the definition of per day per user (pdpu) used in an earlier similar research report (Oulasvirta et al. 2012, 108), and consisted of five aforementioned key indicators.

The mean number of unlocks pdpu was 76,23 sessions, of which 41,92 sessions were Glances. The mean use of the phone was approximately 3 hours and 17 minutes pdpu, and mean of the median single phone usage session was approximately 56 seconds pdpu. The Median SFT between sessions was approximately 17 minutes and 55 second pdpu. Table 8 below presents statistics in more details.

		Unlocks	SOT	Median SOT	Glances	Median SFT
N		2304	2304	2304	2304	2304
Mean		76,23	11852,09	55,52	41,92	1075,16
Median		65,00	9733,72	23,00	32,00	198,00
Std. Deviation		53,073	10659,675	183,081	38,867	11309,462
Percen-tiles	25	41,00	5459,28	14,00	18,00	108,00
	75	99,00	16071,29	41,00	54,00	381,75

Table 8: Frequencies statistics (before HHT) of 78 participants

In order to analyse data generated by the psych app, the time series of each key indicator was processed with Hilbert-Huang Transform (HHT). Using HHT, the time series of SCREEN_ON or SCREEN_OFF events were decomposed into intrinsic mode functions, which were removed from the original signal to reveal the trend of the data over the study period.

4.3.2 Inferential statistics within-subject

The differences in key indicators were tested between the stages of the study for each test subject. This test was done by performing independent-samples t-test using different stages of the study as a grouping variable, and each key indicator as test variable.

There was a significant effect of intervention for SOT between stages 1 (Baseline) and 2 (Capability, with key indicators presented at every unlock), $t(911) = 2,885$, $p < .01$. Between the first two stages, SOT lowered from 3 hours and 40 minutes pdpu to 3 hours and 14 minutes pdpu. The effect of intervention for SOT was also significant between stages 1 and 3 (Motivational), $t(925) = 3,356$, $p < .01$ and between stages 1 and 4 (Goal-attainment), $t(916) = 2,871$, $p < .01$. In the third stage, SOT lowered to approximately 3 hours and 10 minutes, and to 3 hours and 13 minutes in the Goal-attainment stage. The decrease in SOT was not statistically significant when comparing the first stage to the last week, Observation stage, of the study. Changes in SOT are illustrated in Figure 9 below.

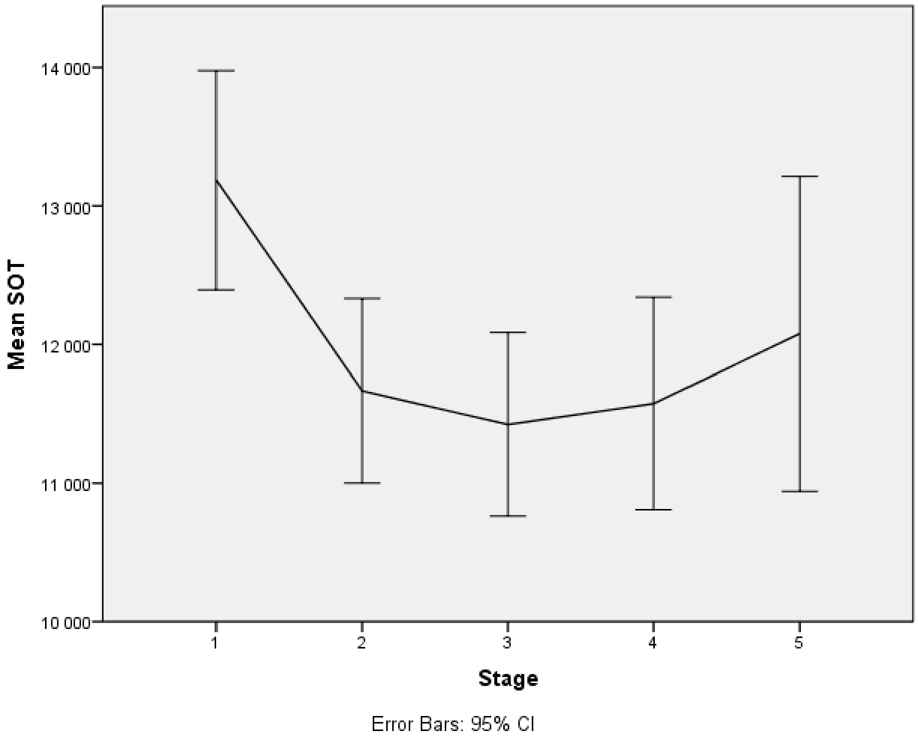


Figure 9: SOT by stage (95% Confidence interval) (after HHT), N=78

The difference in Median SOT was significance between the Baseline stage and Observation stage, t(913) = -2,466, p < .05. The mean duration of individual session increased from 51 seconds pdpu to 92 seconds pdpu. The difference was also significant between Capability and Goal-attainment stages, t(920) = -2,298, p < .05, as well as between Capability and Observation stages, t(917) = -2,945, p < .01. This difference was also significant between Motivational and Observation stages, t(920) = -2,674, p < .01. The mean duration increased from 44 seconds in the Capability stage to 49 seconds in Motivational, to 63 seconds in Goal-attainment and finally to 92 seconds in Observation stage. The changes were not significant between adjacent stages. Figure 10 below illustrates the changes in Median SOT by stage.

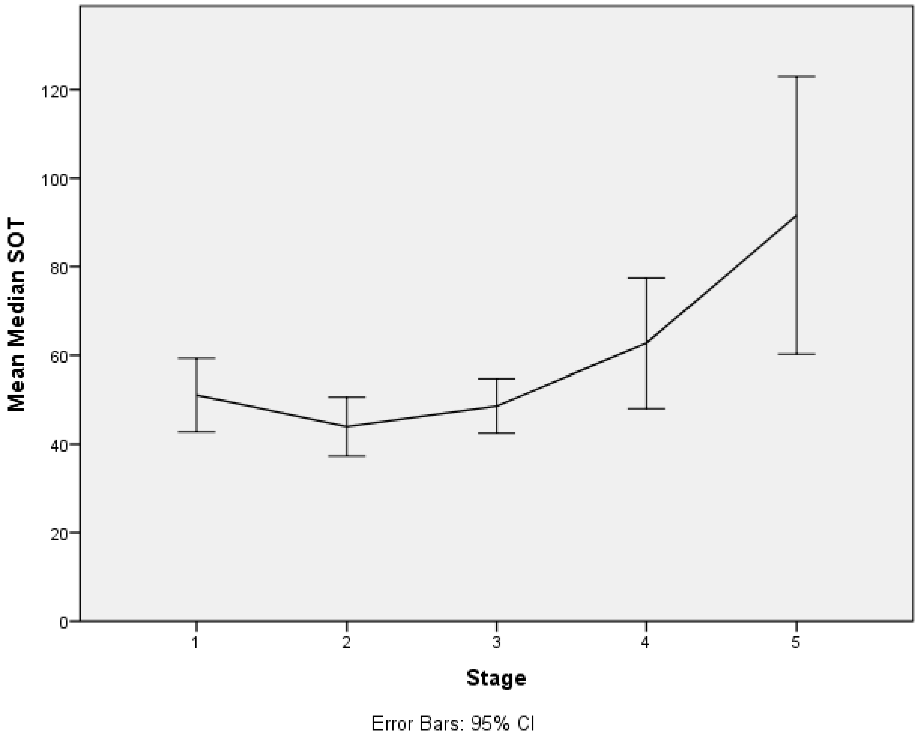


Figure 10: Median SOT by stage (after HHT), N=78

The difference in Glances was only significant between Capability and Observation stages, t(917) = -2,006, $p < .05$. Mean Glances pdpu increased from 41,24 in Capability to 45,55 in Observation stage, illustrated in Figure 11 below.

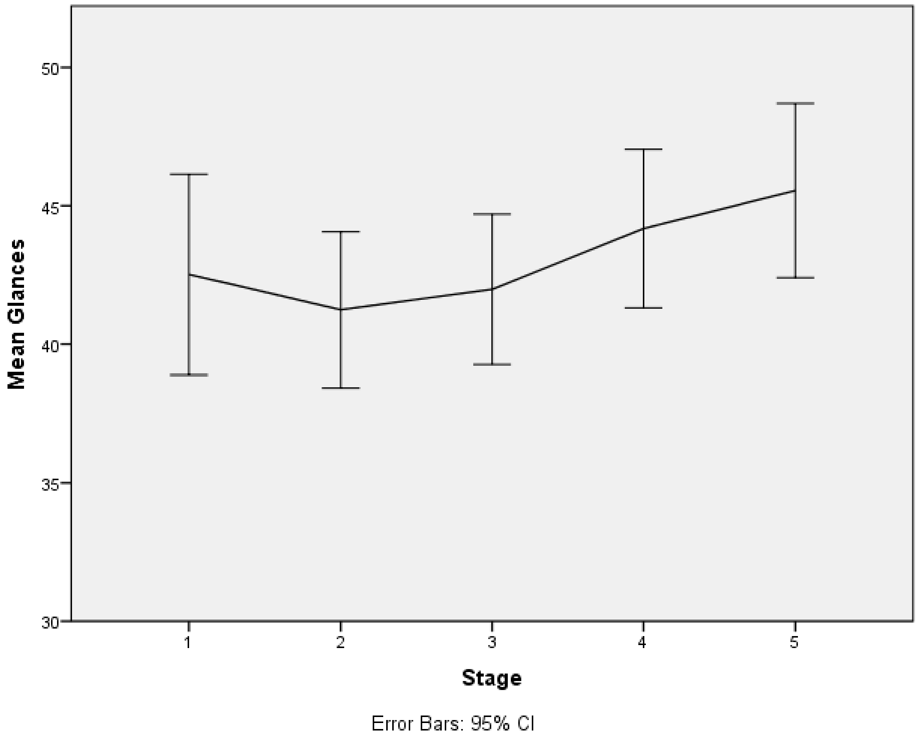


Figure 11: Glances by stage (after HHT), N=78

Simple linear regression was calculated to predict SOT based on Glances. Poor regression equation was found (F(1,2274) = 142,124, p < .000) with an R^2 of .059. Also, simple linear regression was calculated to predict Unlocks based on Glances. A significant regression equation was found (F(1, 2274) = 10188,592, p < .000) with an R^2 of .818.

Median SFT was significantly different between the last two stages when compared to first three stages. Table 9 below illustrates the differences and significances.

From Stage	Goal-attainment	Observation
Baseline	t(916) = 3,194, p < .01	t(913) = 2,815, p < .01
Capability	t(920) = 3,194, p < .01	t(917) = 2,801, p < .01
Motivational	t(923) = 2,299, p < .05	t(920) = 2,491, p < .05

Table 9: Independent-samples t-test of Median SFT by stage (after HHT)

As the non-preprocessed data does not account for the non-linearity and non-stationarity in the phenomenon, the changes in Median SFT after HHT can be characterised so that Median SFT in stages 1, 2 and 3 are not significantly different from each other, but they are markedly higher than in the last two stages. The below Figure 12 illustrates the trend of change in Median SFT by stage.

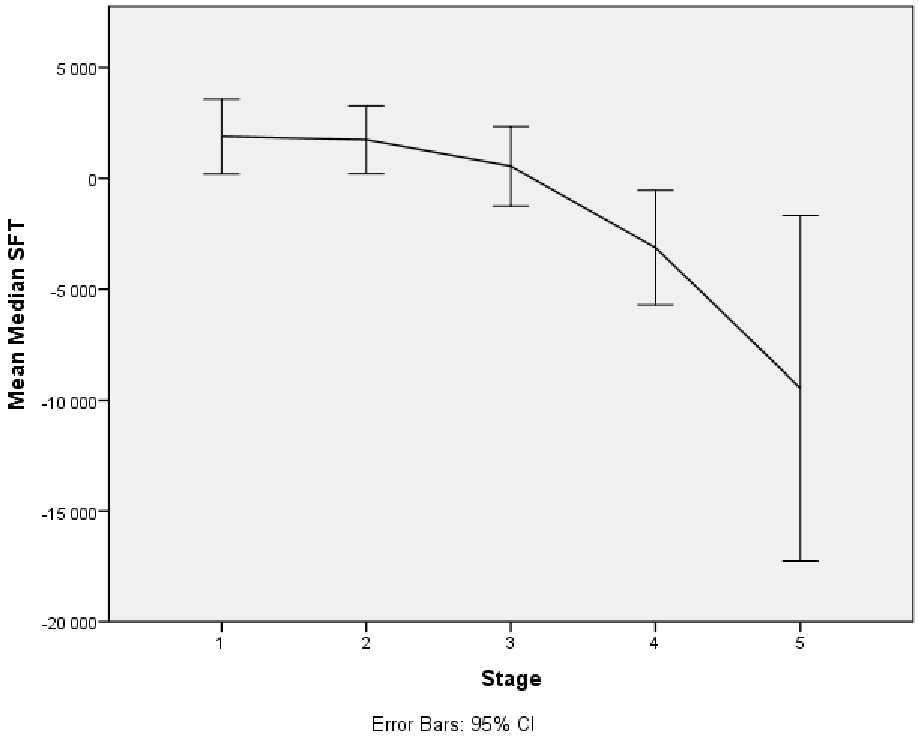


Figure 12: Median SFT by stage (after HHT), N=78

There were no statistically significant differences in unlocks between stages.

4.3.3 Inferential statistics between-subjects

Between-subjects differences in the results were tested to detect differences in phone usage behaviour using Independent samples t-test with each of the five key indicators of smartphone usage as a dependent variable. Group number was used as the grouping variable, and the key indicators were used as test variables. It was assumed that the grouping formed from SPAI-SF factor scores act as a predictor of the smartphone usage.

There was a highly significant effect of grouping for Unlocks between groups, $t(2274) = -3{,}539$, $p < .001$. Members of the group Low unlocked their smartphone on average 75,14 times per day per user (pdpu), where members of the group High did 82,37 unlocks pdpu. N in group Low was 1155 pdpu and in High 1121 pdpu.

There also was a significant effect of grouping for Median SFT between groups, $t(2274) = 3{,}203$, $p < .01$. For descriptive purposes, difference between Median SFT pdpu using the data before HHT was 26 seconds, being 17 minutes 23 seconds for group High, and 17 minutes 49 seconds for group Low. N in group Low was 1155 pdpu and in High 1121 pdpu.

A simple linear regression was calculated to predict key indicator values from SPAI-SF factor score. The purpose of this test was to find out how much change in the score specific to SPAI factor explains changes in two of the key indicators reported with significant effect above. The highest coefficient of determination, R^2 was less than 0,12, suggesting poor regression. The SPAI factors were therefore considered poor predictors of smartphone usage key indicator levels.

4.3.4 Between-subjects inferential statistics

As a final stage in inferential statistical analysis, analysis of variance was performed. The purpose of this analysis was to identify if there are significant mean differences in one or more of the key indicators when interaction of stages of the study and the grouping of the test subjects formed from the SPAI-SF questionnaire scores were tested. This was performed with GLM Univariate in SPSS using the study stages and grouping of the test subject as fixed factors, and each key indicator as a dependent variable. Table 10 illustrates Mean SOT between groups in stages where the difference was statistically significant.

Stage	Group	Mean	SD	Significance
Baseline	Low	12062,35	8569,45	$p < .01$
Baseline	High	14431,92	8675,84	
Capability	Low	10793,10	7087,75	$p < .05$
Capability	High	12597,74	746,24	

Table 10: Differences in SOT by stage by group (after HHT)

Test of between-subjects effect reported significant main effect of treatment on SOT, $F(4) = 3{,}109$, $p < 0.05$. There was a significant main effect for interaction of Group and Stage on SOT, $F(4) = 4{,}282$, $p < 0.01$. N in group Low was 1155, and 1121 in group High. To investigate the changes in SOT between stages by group in more details, estimated marginal means were produced into a figure as illustrated in Figure 13 below.

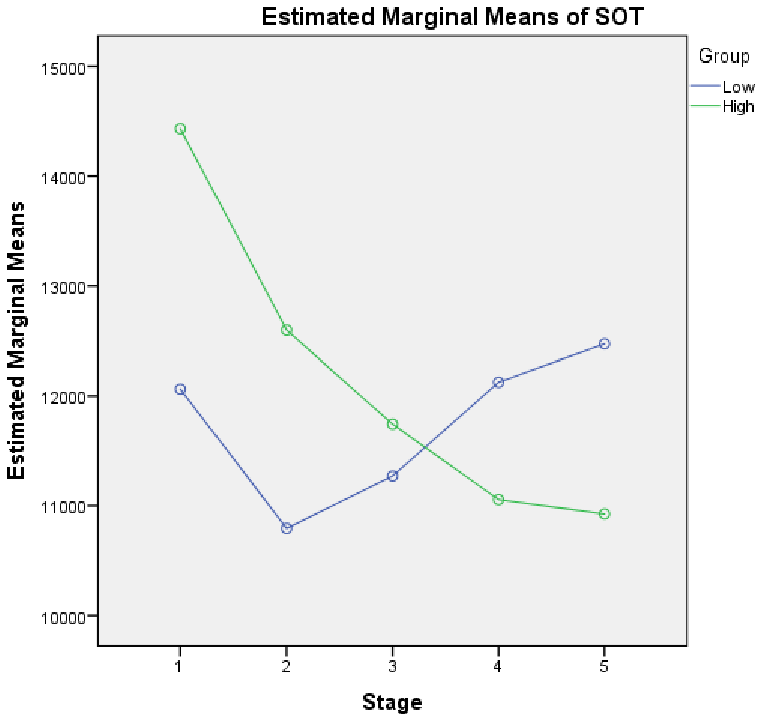


Figure 13: Mean SOT by stage by group, N=77

As can be seen from the figure, SOT pdpu in the Baseline stage and the Capability stage are markedly different, and there is a significant decrease in SOT between the stages. From the Motivational stage onwards, differences between groups were statistically non-significant.

Test of between-subjects effect also reported highly significant main effect of treatment on Median SFT, $F(4) = 6{,}071$, $p < 0.001$. There was a significant main effect for interaction of Group and Stage on Median SFT, $F(4) = 5{,}965$, $p < 0.001$. N in group Low was 1155, and 1121 in group High. Table 11 illustrates Mean Median SFT between groups in stages where the difference was statistically significant.

Stage	Group	Mean	SD	Significance
Goal-attainment	Low	953,99	3734,50	p < .05
Goal-attainment	High	-7206,97	39583,11	
Observation	Low	1061,22	2679,74	p < .001
Observation	High	-20475,56	120448,86	

Table 11: Difference in Median SFT by stage by group (after HHT)

The difference in Median SFT was examined in more details with explorative statistics, illustrated in Figure 14 below.

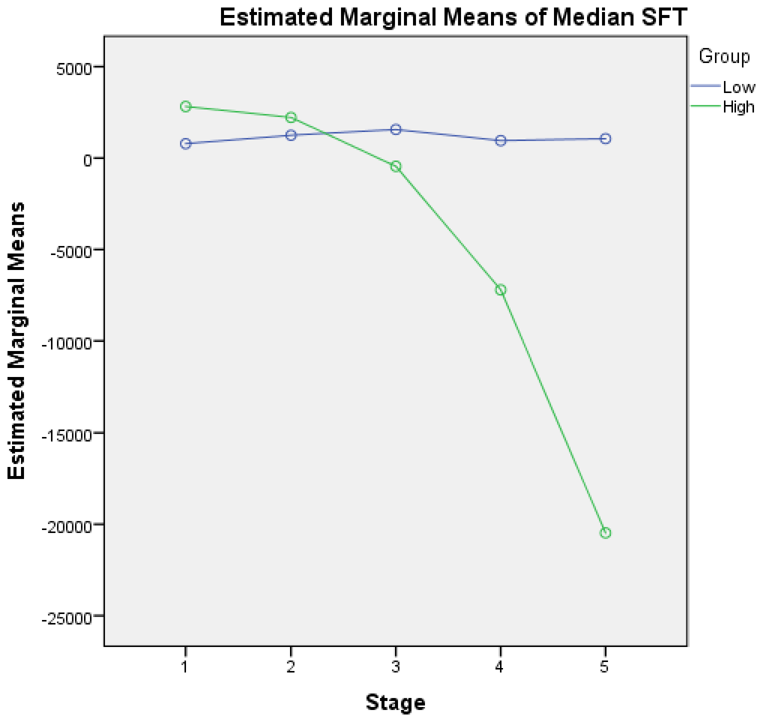


Figure 14: Estimated marginal means of Median SFT by stage by group, N=77

It was discovered that where Median SFT was not markedly different between stages, the decrease in Median SFT was significantly different in the fourth and fifth stage in the group High.

5 Discussion

This thesis focused on four questions. Firstly, to find out how SPAI-SF associates with the smarphone usage. Secondly, if smartphone usage can be nudged to a lower level, and what is the difference in effect depending on the type of nudge. Thirdly, how does the effect of nudges differ between the groups. The final question was if there is a relapse in smartphone usage after the nudges are no longer present.

Each of these four questions are reviewed in more details in the following four sections. This chapter also describes the limitations in this thesis and presents ideas about how to improve and follow up this thesis. Finally, implications and future development ideas in the field of psych app and nudges are discussed.

5.1 Association of self-assessment to smartphone behaviour

The results from this thesis suggest that the SPAI-SF score has association with the characteristics of the smartphone use: statistically significant differences was detected between groups Low and High clustered based on the SFAI-SF factors. When each five key indicators were tested for between-subjects differences based on SPAI-SF factor scores, differences between the groups were highly statistically significant in all key indicators except Median SOT. Mean difference in unlocks between the groups was 12,63 unlocks per user per day, the mean difference in SOT was approximately 36 minutes pdpu. Higher mean values were all in the High group. Mean of Median SFT was approximately 49 seconds lower in High group.

Where the normalised SPAI-SF range was adjusted between 0—40, the results of the test subjects varied between 5,09—28,78. The SPAI questionnaire including 27 questions report used the same method of, but due to the different number of questions, and that the used range was not normalised, the results could not be reliably compared on a total score level. However, when responses to SPAI-SF are compared with SPAI, certain differences to the reference group can be observed.

By estimating the differences in SPAI-SF and SPAI on a descriptive level, the first and the third question had the highest difference exceeding the reference research; questions ten and eight differed the most to the negative side. The standard deviation of the SPAI-SF results were consistently higher than in the reference research by Lin et al. (2014). One reason could be a substantially smaller sample size than in the reference research. By increasing the sample size of the demographics in this thesis, the deviation of the responses may have lowered. As the original results are not available on an individual respondent level, it was not possible to test the statistical significance of the differences. As the Cronbach’s alpha was considered adequate for the study, the results were suggesting differences in the test subject samples between the original SPAI research and this thesis.

Some previous research projects (Tossell et al. 2015; Montag et al. 2015b) have used the methods of psychoinformatics to collect smartphone usage information. These research projects have observed the usage of different smartphone applications (e.g. telephony, Internet browsing or messaging), and the phone usage time was often reported as descriptive statistics. Often times very little inferential statistics about the macro-level insights of the phone usage have been reported pertaining to phone usage times or phone unlocks. Tossell et al. reports mean phone usage time per hour (8.02 and 4.80) and standard distribution (4.13 and 4.80) for addicts and non-addicts respectively; Montag et al. (2015b, 3) reports mean typical smartphone usage (161.95 minutes, SD 83.36).

The between-subjects test helped better understand if indicators calculated from the addiction questionnaire are associated with the smartphone usage. Results showed that the test subjects that received higher scores from SPAI-SF used over half an hour more smartphone per day. According to Nielsen's (2016, 4) report on media consumption, average US consumer spent 1 hours and 39 minutes on smartphone per day. Comparing the half an hour difference between the groups to the average time in Nielsen's report, the difference can be considered rather substantial. Tossell et al. (2015) have previously examined smartphone usage behaviours and the users' relations to smartphone addiction. As the test subjects were grouped together based on their agreements to presented survey, users classified as Self-reported Addicts used phone at least twice as much compared to Non-Addicts. It was not reported by Tossell et al. if the responses were used to predict smartphone behaviours. This prior evidence would suggest that the findings from this thesis are compatible by earlier research reports, and that SPAI-SF is a suitable measurement relating to the smartphone usage behaviour.

The differences in the SPAI-SF results were contrasted with the other research reports that use similar factors to determine the characteristics of an addiction. Lopez-Fernandez (2013, 23) reports that "the symptoms that stood out most were Loss of control and Conflict in PIU, and Withdrawal in PMPU". It is not completely evident that "loss of control" in Lopez-Fernandez' report complies to the definition of "Compulsive behavior", but as this connection has been extensively studied in psychiatry (Henden, Melberg & Røgeberg 2013), it was seemed as the most appropriate association. Conflict mentioned by Lopez-Fernandez was not an addiction factor in Lin et al.'s study. However, the definition of Conflict by Griffiths (2005, 195) suggests similarities to that of Compulsive behaviour factor. The score of Compulsive behaviour was higher than Functional Impairment and Tolerance with high significance, as was Withdrawal higher than Functional impairment. Based on the similarities in the results, it can be suggested that the results from SPAI-SF in this thesis support Lopez-Fernandez's research results on PIU, and that these two factors are important when determining PIU as well as PSU.

A proposition has been established before that the recorded behaviour more strongly associates with smartphone addiction than the self-reported variables (Montag et al. 2015a, 439; Lin et al. 2015). It has also been demonstrated that self-assessment questionnaire can be a powerful tool to identify smartphone addiction (Lin et al. 2014, 4–5). However, little research can be found to investigate the effect of interventions to the smartphone usage. Additionally, as much of the previous research has focused on supporting the diagnostic process of PIU or PSU, this thesis contributes to the existing research by providing new information regarding the effect of interventions to help lower smartphone usage irrespective of the status of addiction, and to help trigger a behaviour change. The results from this thesis suggest that SPAI-SF score can be associated with the characteristics of the smartphone usage.

Even though it was possible to successfully cluster test subjects based on SPAI-SF score and to identify statistically significant mean differences in different key indicators, poor regression equation was found when simple linear regression was calculated to predict SOT based on the SPAI-SF score. Therefore, this thesis does not provide evidence that the self-assessment alone could act as a predictor for the key indicator levels, or that it could be used to identify individuals susceptible for PSU.

Unlike earlier research by Lin et al. (2015), this thesis did not assess test subjects with psychiatric diagnoses, and therefore the results are not connected to the diagnostic criteria of smartphone addiction.

5.2 Using nudges to lower smartphone usage

The second research question asked if the phone usage can be nudged to a lower level without coercive measures. There was a significant main effect for SOT between the Baseline stage and all of the three stages with the nudges. This suggests that by bringing the key indicators into the attention of the smartphone user, a behaviour change can happen.

Reflecting the change in SOT to Michie et al.'s (2011) COM-B framework, the first change could be associated to an increased capability of an individual to observe their phone usage. In the Capability stage of the study, the intervention included information pertaining to the user's phone usage, and according to Hansen & Jespersen's (2013, 21) definition of type 1 transparent nudge, this could have influenced test subjects' automatic behaviour. The effect in SOT was significant for both group Low and High, as well as for the difference between the groups. This suggests that the effect of nudge was significant enough to overcome the inhibiting effects of possibly underlying PSU. The results suggest that nudges can help trigger automatic reflection of smartphone use, or similar process, due to which the SOT can lower.

SOT per day (162 minutes) is in line with what Oulasvirta et al. (2012, 109) reports, but it is only 62,3 percent of what Lin et al. (2015, 142) reports as a median daily use time. Reasons that can explain this a variance in daily phone usage time may be hard to identify. Montag et al. (2015a, 439) have written that where substantial part of the sample in Lin et al.'s (2014) study was characterized as being smartphone addicted, the sample in Montag's research was deemed more within the normal usage range. The researchers also report that the data set ranged in a much limited range than what the total range of the scale used would allow. In the light of this evidence, the absence of extreme results in this thesis may suggest that the results were collected from the sample that did not include substantial amount of problematic smartphone users or smartphone addicts. Lin et al. (2015, 140) report that the recruitment strategy in their study was "based on the potential higher penetration rate of smartphone use". While this recruitment strategy may result to an active and therefore a useful sample, there may be a possibility of inadvertently recruiting individuals that have higher probability of becoming labelled as smartphone addicts. By expanding recruitment strategy to public audience, the sample may consequently expand to include also individuals with moderate or low smartphone usage habits. Although one possible reason is cultural variability between the countries in which the studies were conducted, only two research reports does not provide enough support for this hypothesis.

5.3 Comparing effect of nudges to smartphone usage

The third research question asked if some nudges have stronger effect in influencing improper phone usage. It is not possible to conclude that the one type of nudge can be of higher significance to smartphone behaviour than the other. Statistically significant decrease of SOT between the Baseline stage and both the Capability stage and the Motivational stage suggests that by using nudges that increase capability or motivational components can result to influential behaviour change. However, based on an evidence collected in this thesis, there was no significant change in any of the key indicators between different types of interventions.

Locke and Latham (2002, 714) have earlier suggested that "the effects of goal setting are very reliable". Michie, Atkins and West (2014, 211) have also reported that the interventions with "explicit targets and actions plans to feedback" had a higher impact compared to the interventions without targets. According to Locke and Latham, failures to replicate the effects of goal settings can be due to many reasons, including for example lack of feedback, lack of commitment or failure to match the goal to the performance measure. It is possible that the key indicators used in this thesis do not mediate smartphone usage behaviour. Also, by only providing positively valenced feedback about the goal attainment, but suppressing the negatively valenced feedback about the failure to attain a goal can explain why this thesis could not successfully replicate the effects of goal setting.

Median Unlocks 65,00 pdpu observed in this thesis was 12 percent lower than the daily frequency reported by Lin et al., and almost two times that of what Oulasvirta et al. reports in their paper. There were no statistically significant differences in mean unlocks between the stages of the study. Haug et al. (2015, 304) have earlier found that the smartphone addiction can be better indicated by the duration of use and time until first time in the morning. This is also supported by research concerning the Fear of Missing Out (FoMO), suggesting that people with higher level of FoMO had a tendency to use social media more immediately after having woken up (Dossey 2014, 1847). However, it was not possible to find prior research reports that would have tested the association of different nudges to mean number of unlocks.

The median number of Glances (32,00) in this thesis is over 10 times more than 3,39 SIRBS pdpu reported by Oulasvirta et al. (2012, 108). It should be noted, that the definition of SIRB in the benchmark report included a notion about the type of application: “at least 50% of the usage session duration is spent interacting with applications that provide the reward values”. The definitions for the short sessions are not therefore fully compatible between the research reports, and extensive care should be applied when comparing these numbers.

It was not possible to find a report that would have included at least descriptive statistics about the Median SOT or Median SFT. In this thesis, Median SOT was 23 seconds, and Median SFT was 198,50 seconds (approximately 3 minutes and 19 seconds). These numbers were calculated over the 24-hour period, and therefore they do not account for an expected phone usage pattern where smartphone user would keep their phone unused during the sleep. Due to the missing benchmark reports, these numbers provide little basis for inferential or comparative analysis in reference to the other evidence.

It is worth noticing, that neither Median SOT nor number of unlocks lowered significantly between the Baseline and Capability stage. There are multiple approaches to explaining this phenomenon. The first explanation is that there was a mere measurement effect from the beginning of the study, and the users therefore made an effort to generally lower the amount of engagement with the phone throughout the study by spending less time with the phone at each unlock. Another explanation is that the users generally reflected their phone usage, and did not unlock the phone as often as before. In this case, as soon as they would engage with their phones, they would spend approximately same amount of time with their phone, but that would happen less often. The changes can, however, be so small that it does not significantly change the number of unlocks or median SFT between the stages. If the latter assumption was true, it would suggest that automatic goal may have triggered users to reflect their phone usage before they engage with the phone. As SOT was significantly or highly significantly lower in all stages of the study compared to the Baseline stage, the observation could be a sign of learning in the phone usage behaviour resulted by the interventions.

Median SFT was also significantly or highly significantly lower from Motivational stage onwards compared to the baseline. Unlike SOT or Median SOT, lower level of Median SFT suggests an unfavourable development in phone usage. If the engagement with a phone had developed favourably during the study, Median SFT would have increased, suggesting longer periods of inactivity between the sessions.

Several reasons can exist for the changes in Median SFT. Even if Median SFT lowered from the Motivational stage onwards compared to the baseline for group High, at the same time SOT lowered significantly compared to the baseline for all users. This suggests that test subjects reduced their screen time overall even if they engaged with their phone more often. This was also seen in Median SOT, which was higher in the Goal-attainment and Observation stages to the Capability stage. In the Goal-attainment stage the nudge was built on Motivational component in COM-B framework, proposing that explicit goal is associated with lower phone usage. Evidence referred by Klasnja (2009, 339) have proposed that the automatic goal activation can be triggered with presentation of salient information. It is possible that the differences in the treatments were too small to overcome the familiarity of the intervention from the previous stage, and that the incremental changes in the interventions did not trigger additional ways of behaviour change beyond what was already active from the Capability stage onwards.

Based on this thesis and evidence from prior research reports, it cannot be fully concluded that difference in the type of nudge associates with difference in number of unlocks or glances per day. Even if there was statistically significant different in the mean number of Glances between the Capability and the Observation stage, current literature does not suggest possible explanations for this finding. More literature research and evidence would be required to prove that the absence of an intervention after it has been in effect would trigger the increase in the key indicator.

5.4 Achieving a long-lasting behaviour change

Finally, the fourth question asked if a permanent behavioural change can be attained even if the nudge goes away. The decrease in SOT was not statistically significant when comparing the first stage to the last stage of the study. However, the difference in Median SOT was significant between the Baseline stage and the Observation stage. The mean duration of individual session increased from 51 seconds pdpu to 92 seconds pdpu. Also, the difference in Glances was only significant between the Capability stage and the Observation stage, and Mean Glances pdpu increased from 41,24 in the Capability stage to 45,55 in the Observation stage. Median SFT was significantly different between the Goal-attainment and the Observation stages when compared to the Baseline, Capability and Motivational stage, as illustrated in Table 1 and Figure 14.

According to these results, a systematic relapse in behaviour was seen after the interventions were no longer in effect. However, when mean SOT was compared between groups, group High had a lowering trend even after the interventions, whereas group Low regressed to a higher level of SOT compared to the baseline. Block (2008, 306) has earlier reported that the individuals with internet addiction are resistant to treatment and tend to relapse at a high rate. The findings from this thesis are compliant with Block’s suggestion, although in this thesis it is not possible to associate the findings to a relapse based on psychiatric diagnosis.

As it was also shown in this thesis, the intermittent glancing of the phone increased after the interventions compared to the Capability stage. However, it is not clear if this can be interpreted as a relapse to the previous habits. Oulasvirta et al. (2012, 105) discuss about the “checking habit”, and the 23 seconds Median SOT alone measured over the entire duration of this thesis suggests compatibility with Oulasvirta et al.’s “checking habit”, defined as “brief, repetitive inspection of dynamic content”. This would suggest that the introduction of type 2 transparent nudge neither lowers Median SOT nor Glances, but as soon as the intervention no longer exist, the phone usage will increase substantially.

Klasnja et al. (2009, 339) refer to literature, according to which environmental clues can activate automatic goal activation. The nudges used in this thesis were designed to trigger goal activation on the Goal-attainment stage, but as the Capability stage was the first stage of the study with an intervention, it may be possible that the intervention triggered automatic goal activation. It can be theorized if the goal was automatically defined by the test subject to maintain or lower currently perceived usage level. While this could support unchanged amount of glances throughout the experiment, it is not evident what triggered increase in the mean number of glances in the Observation stage.

There was a significant difference in Median SOT between the Baseline stage and the Observation stage, as well as between Capability and Goal-attainment, between Capability and Observation stages, and between Motivational and Observation stages. In all of these comparisons, Median SOT increased in the Observation stage. It is not known what triggers people to engage with their smartphones almost twice as long at the time in the Observation stage compared to the Baseline, or almost 50% longer at the time compared to the Goal-attainment stage. Oulasvirta et al. (2012, 107–108) have earlier concluded that the increased “checking habit” is associated with higher phone usage overall. Writers suggest that short sessions act as a “gateway” for other content on the device, and that they can be seen as a proxy for habitual usage. While it is unclear if increase of both Median SOT and Glances are due to the latent demand of the content or interaction that would taper out in the course of time, or a permanently elevated level of usage, the absence of any type of intervention seems to be associated with the elevated usage.

Median SFT was significantly different between Goal-attainment and Observation stages when compared to the first three stages. Median SFT results would suggest that for test subjects in group High, nudging can be counterproductive, as these individuals would engage with their smartphones substantially more often without increasing their Median SOT in a statistically significant amount. Davis (2001, 192) has suggested that procrastination has a role in both the development and maintenance of generalized PIU. However, based on the data from this thesis it is not evident if significantly more frequent engagement with the phone is due to these test subjects putting off their responsibilities – as Davis suggests - or due to other reasons.

There was no evidence that nudges can reduce the amount of Glances. Oulasvirta et al. (2012, 113) have suggested earlier that “checking habits may lead to more use overall”. Poor regression equation to predict SOT based on Glances did not therefore support Oulasvirta et al.’s previous findings. However, significant regression equation found when Unlocks were predicted based on Glances would suggest that even though changes in Unlocks were not significant between the stages, they would increase with the increase of Glances as the interventions cease to exist.

Oulasvirta et al. suggest that using behavioural triggers can be used to drive behavioural changes. The concept of Klasnja et al.’s (2009, 342) referred by Oulasvirta et al. (2012, 113) is compatible with the method that was used in this thesis. However, even though this thesis supports both Klasnja et al.’s as well as Oulasvirta et al.’s conclusion that interventions can help trigger behaviour change, this thesis does not support the proposition that interventions can help maintain a behaviour change.

By considering all of these results, it can be suggested that there is a difference in how individuals respond to interventions, and that the SPAI-SF score could act as a proxy to determine the effect of the intervention, which for people in group High could trigger a longer-lasting effect. It can also be concluded that nudges can help trigger automatic reflection of smartphone usage, resulting at least in lower SOT, however, this might come at price of increased intermittent glancing and overall increased usage of the phone when the interventions are no longer present.

5.5 Limitations

There are several aspects in this thesis that might limit the applicability of the results. The limitations can be categorized to limitations in the theorized assumptions about human behaviour, methodological limitations in the experiment construction, methodological limitations in the data analysis, and to limitations in interpreting the results.

The SPAI-SF used in the thesis was provided in English delivered by the research team, and it was translated to Finnish by the writer of this study. Borsa, Damásio and Bandeira (2012) recommends that in addition of language translation, adaptation should strive for the linguistic, cultural, contextual and scientific balance in the adaptation between languages. The writers also suggest back-translating the translated and adapted instrument to its original language in order to review the extent to which the adaptation has influenced to the original language. While the translation of the research questions from English to Finnish was performed carefully, and special focus was given to preserve the nuances of the questions, necessary resources were not available to follow recommendations from the literature. Therefore, the cultural adaptation of SPAI-SF to Finnish may acts as an unknown regressor in the SPAI-SF results.

The test subjects to this thesis were recruited through social networking, personal contacts and by enabling enrolled test subjects to refer to the psych app in the Google Play store from the application itself. Therefore, it can be expected that people who had curiosity or interest towards the smartphone usage were overrepresented in the sample. In the same way, the thesis worker recruited personally tens of test subjects amongst him friends, families and extended circles of people. It is not known how many individuals who are ambivalent towards the topic under research agreed to install the application and participate to the research for altruistic purposes, but it can be assumed that the sample of the test attendees were generally biased towards people with positive valence towards the topic under research. Further studies should strive to recruit test subjects varying in the degree of which they express valence towards the research topic. Also, the recruitment method should minimize the familiarity to the researcher, in order to decrease the expected social desirability bias. These reasons would also suggest that there is a response bias due to the non-attendees who might be more ambivalent towards the topic under research, and could possess different smartphone usage characteristics. Further, the valenced attitude towards the topic under research, and a possible personal connection to the researcher can be expected to increase social desirability bias, a desire to behave in ways that they expect researcher to prefer (Norwood & Lusk 2011, 528).

Finally, It is not clear how much the behaviour of the test subject is influenced by the so called mere-measurement effect, according to which measuring intentions increase attitude accessibility (Morwitz & Fitzsimons 2004, 73). Morwitz and Fitzsimons (2004, 64) have reported that by measuring attitudes, they become more accessible and will influence choices.

It is possible that the mere measurement effect can influence the results of this thesis at least in two ways. By prompting test subjects to consider their smartphone addiction, their self-consciousness for smartphone usage and its effects may raise. This may result to responses that demonstrate the desired future behaviour of the test subjects rather than their actual past behaviour. Therefore, it is possible that the smartphone behaviour during the days following the questionnaire may be influenced by the responses. This can introduce a noise to the data. Secondly, it is possible that by being aware that their smartphone usage is being measured, the behaviour of a test subject is changed. In this particular study, due to the technical reasons, an icon of the psych app was placed permanently to the smartphone user interface. This icon may have further elevated the mere measurement effect, introducing further noise to the data. Due to these reasons, it should be considered if the related addiction questionnaire should be either conducted both at the beginning and at the end of the study, introducing a delay between the questionnaire and the beginning of the study, or if the questionnaire should only be available to a subset of test subjects.

The research assumptions were built on the COM-B behaviour change model from Michie, van Stralen and West (2011). Some references discuss the potential, as well as problems, of using smartphone applications to help design and deliver behaviour change interventions (Michie 2015b, 34, a, 10–18; Garnett, Crane, Michie, West & Brown 2016), however all of the examples use smartphones to help address specific addiction other than such pertaining to the use of smartphone per se. Therefore, it is not known if COM-B model has been used earlier to construct behaviour change interventions that try influence to people’s smartphone usage rather than trying to use smartphone as a tool to deliver behaviour change interventions towards other types of addictions.

When selecting the most effective intervention, Michie et al. recommend to consider the full range of behaviour change techniques, and identify the most suitable interventions from the full list of potentially applicable interventions (Michie et al. 2014, 150). In this thesis, the purpose was to explicitly investigate how interventions that build on the concept of nudge (i.e. voluntary, avoidable, exempt of financial incentive) could help lower smartphone use. Due to this scoping, it is unknown if better interventions could be identified, and if better results could be achieved by using COM-B framework with the full selection of available behaviour change techniques.

Several limitations exist in this thesis due to the hypothesized human behaviour. The interventions in this thesis used positively valenced feedback. Fishbach, Eyal and Finkelstein (2010, 518–519) have shown that while positive feedback is an effective way to signal participants their increased commitment to pursue the desirable goal, it has also been demonstrated that negative feedback is more effective in cases where it signals a lack in goal progress. Considering the Motivational and Goal-attainment stages in this thesis, the feedback was valenced based on the goal progress. In the Motivational stage, if a test subject had increased the smartphone usage compared to the equivalent period in the previous stage, providing negatively valenced emoticon would have been more compatible with Fishbach et al.'s findings, signalling lack in goal progress. In the same way, failing to lower the smartphone usage in the Goal-attainment stage compared to the equivalent period in the Motivational stage resulted to the lack of valenced feedback. Providing negatively valence feedback would have been more explicitly associated with the goal progress.

The key indicators of smartphone usage were based on the number of unlock events of the phone, and for how long the phone were kept unlocked or locked. However, in order for a behaviour change to occur, the smartphone users would have to either learn away from a previous habit of intermittently unlocking their phone, or they would have to actively deliberate whether unlocking their phone is necessary. As the interventions were delivered from the application running in the smartphone, the user only became subject to the interventions once the usage had already happened. This thesis does not provide insights if delivering an intervention in the physical or psychological environment outside the phone can help lower smartphone use. One of these interventions could be to provide a physical pouch or flip cover, increasing the burden of engaging with the phone.

The application that was used in the thesis had numerous technical limitations. Firstly, the application was purposely limited to only keep track of unlock and lock events and their times. This excluded notifications that may influence to the use of the phone, including the user of vibration, led signal, or sound alert in the event of e.g. new text message, new email, or a social network activity. This thesis does not provide evidence if presence or absence of some of the notification type influence the key indicators of this thesis. In the same way, the application did not track the smartphone applications that the test subjects used, and therefore the phone usage cannot be attributed to specific application.

It is widely understood that the social context, desire to stay connected with people in cyberspace, and the fear of missing out influence to the use of phones (Humphreys 2005; Przybylski et al. 2013; Krishnan et al. 2014). However, this thesis did not account for the social context, situation in which the test subject was while using the phone, the time of a day, or whether the use of phone happened in business or personal situation. It is therefore not known to what extent social situations influenced the phone usage, or whether interventions had bigger influence to phone usage in specific social context.

While the cloud computing platform used in the thesis collected demographic information of the test subjects, including their country, age cohort, gender, and interest towards specific categories such as Arts & Entertainment, Autos, Online communities, the research information sheet did not inform users of these background variables. Therefor this information was not utilized in the thesis. Except for the time zone and certain technical phone information, the application developed for this research did not collect background variables from the users. IT is therefore unknown how much age, gender, home country or interest towards specific topics explain the behaviour change.

Path dependence, a dynamic process that is dependent in its own history, has been widely researched (Altman 2000; David 2005), and one of the key challenges in path dependent research has been suggested to lie in its ambiguity in proving the single factor that explains the observed phenomenon. This thesis was constructed on the basis of providing one set of successive treatments for all test subjects. In the first week, the psych app observed the test subject's behaviour to provide a baseline of their behaviour. During the successive three weeks, the test subject received three types of interventions, one intervention type per week. During each week, the reference point was selected from the previous week. In order to receive positively valenced feedback, the user had to lower their smartphone usage, introducing path dependence between the stages with the nudges. In the Observation stage, the test subject was again observed for possible relapse.

In the context of this thesis, the essential path dependence between the Capability, Motivational and Goal-attainment stages can be suggested to influence to the result of the Goal-attainment stage, and therefore the reference point for the Observation stage can be considered a path dependent outcome (David 2005, 6). It is unknown how the smartphone usage of a test subject would have developed in circumstances where the order of the stages would have been different, or if there had only been one or two of the stages present during the study. This limitation could have been addressed by performing a randomized controlled trial, where the order of the stages would have been varied, or where individual test subject would have only experience exactly one type of intervention.

During the study, some test subjects reported abnormally high usage times. Upon further engagement to investigate the symptom, it was discovered that these individuals used so-called screen saver applications that show information on the phone screen even if the phone is not used. Depending on the way these applications were developed, the time during which the phone was not used was reported as usage time. Due to the limited ways in which the psych app could collect information pertaining the use of phone, it is possible that the use of such application introduce noise to the data, but there is a little amount of ways to reliably detect this noise. Some test subjects also informed that they use their phone as a watch to check time of day from the phone screen. As soon as these users unlocked the phone screen to check the time, the phone recorded it as an unlock. While short phone usage sessions were used as one of the key indicators of PSU, it is not justifiable to count using phone as a watch as a problematic behaviour. While this behaviour could be controlled in a within-subject tests, the frequent short use of phone with true intention contributed to the between-subjects tests, and can act as a noise in the results.

Finally, the thesis included only five key usage indicators: Unlocks per day, SOT, Median SOT, Median SFT, and Glances. It is not evident that these indicators represent such an inventory of indicators that explain PSU. While indicators based on frequency, duration and median of usage times are similar to the previous research on smartphone addiction (Lin et al. 2014), Oliver (2010) has suggested diurnal patterns as a smartphone usage indicator. Additionally, number of research reports include analyses of the application usage (Lee et al. 2014a; Montag et al. 2015b). Considering that the raw data can be processed easily, and new composite indicators can be calculated, better explanatory factors than what was used in this thesis might be possible to develop.

5.6 Recommendations for further research

Due to the sufficiently high computational power of the modern smartphones, several recommendations can be made to further research PSU. By evaluating the limitations of this thesis, a randomized controlled trial should be considered to exclude the path dependence in the experiment construction, and to better explain what of the interventions are the most effective. Additionally, negatively valenced feedback could be introduced to signify the lack of goal progress.

Although SPAI factors reported as poor predictor of smartphone key indicator levels, it would be possible to hypothesize on the benefits of models that can predict smartphone addiction or PSU based on the phone usage only without questionnaire or interventions. By providing evidence of this regression, it would be possible to develop ways to trigger interventions that specifically address a given maladaptive phone usage, whether that is intermittent glancing, or high SOT.

Short glances to the phone was chosen as one of the key indicators of PSU. Although this key indicator was supported in the earlier studies as a proxy for increased phone usage, none of the nudges used in this thesis could reliably help lower the levels of this key indicator. Future research should explore the effects of negatively valenced interventions, for example by associating an audible warning signal as soon as a short glance session was observed. Using this type of intervention, it would be possible to test if smartphone users avoid short glances in order to avoid a negatively valenced audible message.

Before and during the execution of this thesis, number of papers was found to discuss at length about the internet addiction and its subset, smartphone addiction. These papers also included number of therapeutic interventions, most of which focused on the treatment of diagnosed addiction. However, considering the abundance of proper usage of Internet and smartphones, it is surprising that so little reports can be found to discuss about the prevention of related addictions. Montag and Reuter (2015c, 10, 148) point out that the primary goal of treatment is a moderate level of Internet usage, the recommended ways to detect and intervene abnormal usage focus on specific PIU, triggered by game, gambling, or sex sites. Number of reports that focus on the discovery of the underlying specific addiction behind specific PIU, or an underlying depression (Young 2004, 413; Kim 2013b, 402; Davis 2001, 194).

The social context and social norms were not present in the experiment construction of this thesis. Further studies would be needed to test if social norms could help lower smartphone usage. For example, test subjects could enrol to a reference group of their preference, and the psych app could maintain a scorecard or leader board of the group members based on their smartphone usage or improvement in their smartphone usage.

Beard (2007, 183–184) quotes Marlatt in that the effective treatment can focus on the changing behaviours irrespective of their origin. Beard suggests a set of interventions including of behavioural, cognitive and lifestyle nature. As Internet users are encouraged to detect the limits of fair usage, and learn which triggers cause them to exceed these limits. Subsequently, proper intervention and treatment strategies can help control Internet use, and if so required, seek help. This approach seems to be highly compatible with the experiment applied in this thesis in that the nudges act as interventions to lower specific key indicators depicting generalized PSU independent of the underlying personal reasons of smartphone use. More research would be required to investigate the addictive nature of Generalized PIU without particular underlying addiction often associated with Specific PIU.

5.7 Implications of this study and future development ideas

As it has been reported that the data set generated from smartphone usage information can be of non-stationary or non-linear nature (Lin et al. 2015, 139–140), this thesis used Hilbert-Huang Transform (HHT) in a similar way than it was used earlier in Lin et al.'s (2015) similar research projects. While HHT was used to identify changes in the underlying trend of the data, the benefits of HHT include ability to decompose the signal to periodic components. Depending on the source data, these periodic components can have a real world meaning (Barnhart 2011, 11–13), and therefore it would be possible to analyse, for example, if changes in frequency of sessions of specific lengths are being replaced with sessions of different lengths. It might also be possible to present these results as a Hilbert Spectrum to improve visual illustration (Huang, Chen, Lo & Wu 2011, 82). This thesis contributes to earlier information that statistically reliable results can be inferred from the data set processed with HHT.

Much of the reference literature deal with the problematic or addictive smartphone use. Davis (2001, 193), however, brings up a point of view to the context of this discussion by contemplating the distinction between healthy Internet use and the use of Internet in a pathological way. The paper suggests that the Internet use is a "continuum of functioning" between unhealthy and healthy Internet use. As no commonly agreed thresholds for addiction exists, the unhealthy use is essentially a question of whether the usage is adaptive or maladaptive.

It has earlier been reported that the smartphone research participants are unable to estimate their phone usage in relevant accuracy (Montag et al. 2015a, 439). This study demonstrated that psychoinformatics can help record the real information generated from the real world, instead of using self-reported information for inferential analysis. Researchers with necessary programming and software development skills can create applications for specific research purposes, and infer statistically significant results. Instead of focusing to the development of the research setting and data collection from a constructed experiment, the research approaches using psychoinformatics can help collect larger or longitudinal data sets as a by-product of the real-world scenarios. This also helps focus on data analytics. The approach has been earlier named as computation social sciences, and it can help combine the necessary precision of the research data with everyday world (Chang et al. 2014, 68; Markowetz et al. 2014, 410–411). Using iterative software development methods, it is also easier to extend simpler research constructs with tests such as difference-in-difference tests between groups or randomized controlled trials.

One of the focus areas in this thesis was to perform the interventions (i.e. the nudges) using the application running on the smartphone. In the light of continuum of functioning introduced by Davis, with the help of psychoinformatics it would be possible to develop applications that take advantage of the concept of nudge, and deliver them on the smartphone without trying to lower generalized PSU. Two examples are proposed below.

Phone usage while driving is illegal in many countries, and although it has been shown that using a phone while driving competes for the attention of the driver and presents a safety risk, the behaviour has not been included to the smartphone addiction indicators (James 2012, 125). A paper has been released by World Health Organization (2011), in which several interventions are recommended to address smartphone usage. However, the interventions are exclusively limited to enforcing laws, running public informative and coercion. Further research should be made to test the effect of nudges to lower phone usage while driving. The application developed for this thesis could be modified to present smartphone user with a visual notification if the smartphone was used while it is moving faster than walking speed, depicted in Figure 15 below.

Figure 15: Nudge to notify smartphone user while driving

It has also been shown that checking messages during face-to-face social interactions has number of negative outcomes. This can lead to relatively worse outcomes of the negotiation, but also decrease the perception of trustworthiness and level of professionalism experienced by the negotiating other party. (Krishnan et al. 2014, 203.) More research should be conducted to develop interventions that help people focus on their counterparts in here-and-now social situations. One possible intervention is to extend the application used in this thesis to at every unlock verify if the smartphone user's calendar has an appointment scheduled with more than one person at the time, as depicted in Figure 16 below. If the conditions were true, the intervention built on the purpose would prompt the user to focus on the situation in the real world instead of in the cyberspace.

Figure 16: Intervention prompting to focus on a real-world situation

The application developed as part of this thesis has been licensed under Apache License 2.0. This license permits the use of the resulting application and the source code for personal, corporate or commercial purposes (Apache Software Foundation 2016). As such this thesis contributes to the expanding software library of psych apps. As the psych app used in this thesis and its source code can be freely used for both commercial and research purposes, the barrier entry cost of researching nudges and behaviour change may lower. As a result, this thesis can possibly make researching behavioural economics and nudges more attractive for other researchers. The new applications and software products leveraging the information available about behavioural economics and the effect of nudges can potential help people improve their own well-being and relationships in both cyberspace and here-and-now.

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Figures

Tables

Appendices

Appendix 1: Smartphone Addiction Inventory Short Form (SPAI-SF) questions

Below is a list of smartphone-related behaviors or responses people sometimes have following their smartphone using experiences. Please read each item carefully, and select the option that best describes how much the description fits you **during the past 3 months**.

1. Although using smartphone has brought negative effects on my interpersonal relationships, the amount of time spent on Internet remains unreduced.
2. I use smartphone for a longer period of time and spend more money than I had intended.
3. I try to spend less time on smartphone, but the efforts were in vain.
4. I feel aches and soreness in the back or eye discomforts due to excessive smartphone use.
5. I make it a habit to use smartphone and the sleep quality and total sleep time decreased.
6. To use smartphone has exercised certain negative effects on my schoolwork or job performance.
7. I feel restless and irritable when the smartphone is unavailable.
8. I feel uneasy once I stop smartphone for a certain period of time.
9. I find that I have been hooking on smartphone longer and longer.
10. I have increased substantial amount of time using smartphone per week in recent 3 months.

Appendix 2: SPAI factor loadings

Question	Compul-sive be-haviour	Functional impair-ment	Withdrawal	Tolerance
Although using smartphone has brought negative effects on my interpersonal relationships, the amount of time spent on Internet remains unreduced.	**.837**	**-.092**	**-.114**	**.049**
I use smartphone for a longer period of time and spend more money than I had intended.	**.600**	**-.108**	**.153**	**.156**
I try to spend less time on smartphone, but the efforts were in vain.	**.492**	**.080**	**.321**	**.022**
I feel aches and soreness in the back or eye discomforts due to excessive smartphone use.	**-.143**	**.830**	**-.137**	**.125**
I make it a habit to use smartphone and the sleep quality and total sleep time decreased.	**.031**	**.757**	**.126**	**-.081**
To use smartphone has exercised certain negative effects on my schoolwork or job performance.	**.073**	**.535**	**.183**	**.011**
I feel restless and irritable when the smartphone is unavailable.	**.088**	**-.247**	**.810**	**-.015**
I feel uneasy once I stop smartphone for a certain period of time.	**.257**	**-.345**	**.756**	**.137**
I find that I have been hooking on smartphone longer and longer.	**.032**	**-.086**	**.087**	**.867**
I have increased substantial amount of time using smartphone per week in recent 3 months.	**.092**	**-.002**	**-.106**	**.847**

Figure: Factor loading between SPAI-SF questions and different behaviours

Appendix 3: SPAI-SF validity, reliability and descriptive statistics

Correlations

		Negative interpersonal	Use longer and more money	Try to spend less time	Aches and soreness	Sleep quality and time decrease	Neg. eff on school and work	Restless and irritable when unavailable	Uneasy once I stop using smartphone	Hooking longer	Subst. increased amount of time	TotalAnswerScore
Negative interpersonal	Pearson Correlation	1	,136	,208**	,066	,088	,123	,186*	,166*	,263**	,137	,380**
	Sig. (2-tailed)		,077	,006	,393	,255	,110	,015	,030	,001	,075	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Use longer and more money	Pearson Correlation	,136	1	,363**	,382**	,364**	,259**	,215**	,270**	,373**	,248**	,584**
	Sig. (2-tailed)	,077		,000	,000	,000	,001	,005	,000	,000	,001	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Try to spend less time	Pearson Correlation	,208**	,363**	1	,350**	,327**	,317**	,249**	,385**	,496**	,323**	,652**
	Sig. (2-tailed)	,006	,000		,000	,000	,000	,001	,000	,000	,000	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Aches and soreness	Pearson Correlation	,066	,382**	,350**	1	,378**	,300**	,199**	,223**	,375**	,314**	,587**
	Sig. (2-tailed)	,393	,000	,000		,000	,000	,009	,003	,000	,000	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Sleep quality and time decrease	Pearson Correlation	,088	,364**	,327**	,378**	1	,496**	,259**	,406**	,457**	,327**	,669**
	Sig. (2-tailed)	,255	,000	,000	,000		,000	,001	,000	,000	,000	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Neg. eff on school and work	Pearson Correlation	,123	,259**	,317**	,300**	,496**	1	,317**	,313**	,461**	,374**	,636**
	Sig. (2-tailed)	,110	,001	,000	,000	,000		,000	,000	,000	,000	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Restless and irritable when unavailable	Pearson Correlation	,186*	,215**	,249**	,199**	,259**	,317**	1	,609**	,431**	,174*	,596**
	Sig. (2-tailed)	,015	,005	,001	,009	,001	,000		,000	,000	,023	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Uneasy once I stop using smartphone	Pearson Correlation	,166*	,270**	,385**	,223**	,406**	,313**	,609**	1	,586**	,230**	,680**
	Sig. (2-tailed)	,030	,000	,000	,003	,000	,000	,000		,000	,002	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Hooking longer	Pearson Correlation	,263**	,373**	,496**	,375**	,457**	,461**	,431**	,586**	1	,504**	,799**
	Sig. (2-tailed)	,001	,000	,000	,000	,000	,000	,000	,000		,000	,000
	N	171	171	171	171	171	171	171	171	171	171	171
Subst. increased amount of time	Pearson Correlation	,137	,248**	,323**	,314**	,327**	,374**	,174*	,230**	,504**	1	,584**
	Sig. (2-tailed)	,075	,001	,000	,000	,000	,000	,023	,002	,000		,000
	N	171	171	171	171	171	171	171	171	171	171	171
TotalAnswerScore	Pearson Correlation	,380**	,584**	,652**	,587**	,669**	,636**	,596**	,680**	,799**	,584**	1
	Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	,000	,000	,000	,000	
	N	171	171	171	171	171	171	171	171	171	171	171

**. Correlation is significant at the 0.01 level (2-tailed).

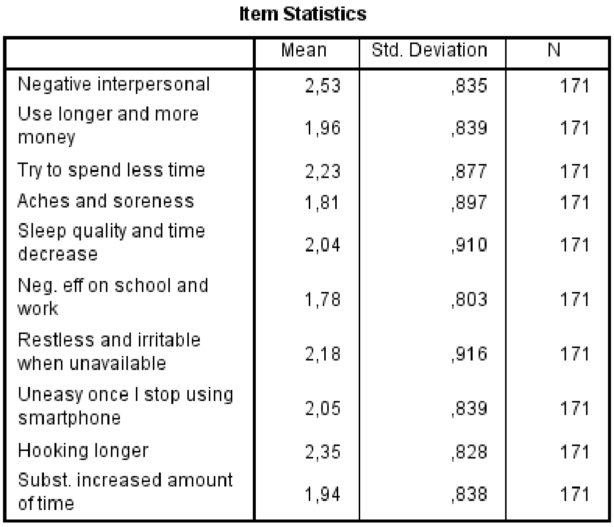
*. Correlation is significant at the 0.05 level (2-tailed).

Table: Validity test: Pearson Product Moment Correlation results

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Negative interpersonal	18,33	25,353	,234	,091	,829
Use longer and more money	18,89	23,530	,464	,255	,806
Try to spend less time	18,63	22,730	,540	,324	,798
Aches and soreness	19,05	23,250	,458	,271	,807
Sleep quality and time decrease	18,82	22,396	,556	,388	,796
Neg. eff on school and work	19,08	23,252	,532	,351	,799
Restless and irritable when unavailable	18,68	23,076	,466	,403	,806
Uneasy once I stop using smartphone	18,81	22,682	,579	,533	,794
Hooking longer	18,51	21,698	,730	,576	,778
Subst. increased amount of time	18,92	23,534	,465	,306	,806

Figure: Reliability test item-total statistics



Item Statistics

	Mean	Std. Deviation	N
Negative interpersonal	2,53	,835	171
Use longer and more money	1,96	,839	171
Try to spend less time	2,23	,877	171
Aches and soreness	1,81	,897	171
Sleep quality and time decrease	2,04	,910	171
Neg. eff on school and work	1,78	,803	171
Restless and irritable when unavailable	2,18	,916	171
Uneasy once I stop using smartphone	2,05	,839	171
Hooking longer	2,35	,828	171
Subst. increased amount of time	1,94	,838	171

Figure: Questionnaire descriptive statistics

The table below summarizes the differences between the results in the reference article and in this research.

Indicator	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
SPAI mean	1,86	1,91	1,86	2,09	1,98	1,89	2,46	2,18	2,38	2,15
SPAI SD	0,69	0,72	0,67	0,77	0,78	0,66	0,8	0,75	0,75	0,8
SPAI-SF mean	2,53	1,96	2,23	1,81	2,04	1,78	2,18	2,05	2,35	1,94
SPAI-SF SD	0,84	0,84	0,88	0,90	0,91	0,80	0,92	0,84	0,83	0,84
Mean delta	0,67	0,05	0,37	-0,28	0,06	-0,11	-0,28	-0,13	-0,03	-0,21
SD delta	0,15	0,12	0,21	0,13	0,13	0,14	0,12	0,09	0,08	0,04

Table: Differences in SPAI and SPAI-SF responses

Appendix 4: Within subject inferential statistics

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Unlocks	Equal variances assumed	5,021	,025	,558	934	,577	1,904	3,411	-4,789	8,597
	Equal variances not assumed			,558	914,983	,577	1,904	3,411	-4,790	8,597
SOT	Equal variances assumed	8,214	,004	2,942	934	,003	1534,742	521,692	510,918	2558,566
	Equal variances not assumed			2,942	905,537	,003	1534,742	521,692	510,876	2558,607
Median SOT	Equal variances assumed	4,640	,031	1,141	934	,254	6,102	5,348	-4,393	16,597
	Equal variances not assumed			1,141	898,515	,254	6,102	5,348	-4,394	16,598
Glances	Equal variances assumed	4,243	,040	,463	934	,643	1,073	2,316	-3,472	5,618
	Equal variances not assumed			,463	883,685	,643	1,073	2,316	-3,472	5,618
Median SFT	Equal variances assumed	,026	,871	,459	934	,647	574,963	1253,843	-1885,713	3035,639
	Equal variances not assumed			,459	933,995	,647	574,963	1253,843	-1885,713	3035,639

Figure: Independent samples t-test: phase 1 vs. phase 2

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Unlocks	Equal variances assumed	8,060	,005	,662	934	,508	2,228	3,368	-4,381	8,838
	Equal variances not assumed			,662	906,720	,508	2,228	3,368	-4,381	8,838
SOT	Equal variances assumed	12,187	,001	3,523	934	,000	1839,580	522,191	814,776	2864,384
	Equal variances not assumed			3,523	906,234	,000	1839,580	522,191	814,735	2864,425
Median SOT	Equal variances assumed	6,080	,014	,512	934	,609	2,652	5,180	-7,514	12,818
	Equal variances not assumed			,512	867,147	,609	2,652	5,180	-7,515	12,819
Glances	Equal variances assumed	4,071	,044	,069	934	,945	,159	2,288	-4,331	4,648
	Equal variances not assumed			,069	870,856	,945	,159	2,288	-4,331	4,649
Median SFT	Equal variances assumed	,160	,689	2,354	934	,019	2974,848	1263,981	494,276	5455,420
	Equal variances not assumed			2,354	933,691	,019	2974,848	1263,981	494,275	5455,421

Figure: Independent samples t-test: phase 1 vs. phase 3

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	9,515	,002	,305	934	,760	1,027	3,360	-5,568	7,622
	Equal variances not assumed			,305	905,164	,760	1,027	3,360	-5,569	7,622
SOT	Equal variances assumed	3,197	,074	2,478	934	,013	1426,833	575,747	296,926	2556,739
	Equal variances not assumed			2,478	932,960	,013	1426,833	575,747	296,924	2556,741
Median SOT	Equal variances assumed	3,896	,049	-1,237	934	,216	-10,417	8,422	-26,945	6,110
	Equal variances not assumed			-1,237	737,233	,216	-10,417	8,422	-26,951	6,116
Glances	Equal variances assumed	2,516	,113	-,797	934	,426	-1,856	2,329	-6,427	2,715
	Equal variances not assumed			-,797	889,193	,426	-1,856	2,329	-6,427	2,716
Median SFT	Equal variances assumed	7,734	,006	3,345	934	,001	7170,371	2143,878	2962,994	11377,747
	Equal variances not assumed			3,345	651,361	,001	7170,371	2143,878	2960,624	11380,117

Figure: Independent samples t-test: phase 1 vs. phase 4

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	8,432	,004	-,558	874	,577	-1,955	3,507	-8,838	4,928
	Equal variances not assumed			-,564	872,600	,573	-1,955	3,465	-8,755	4,845
SOT	Equal variances assumed	13,661	,000	4,393	874	,000	2402,926	546,977	1329,384	3476,468
	Equal variances not assumed			4,442	873,386	,000	2402,926	540,915	1341,282	3464,570
Median SOT	Equal variances assumed	26,461	,000	-2,653	874	,008	-45,550	17,166	-79,242	-11,858
	Equal variances not assumed			-2,497	451,265	,013	-45,550	18,239	-81,393	-9,706
Glances	Equal variances assumed	,988	,320	-1,539	874	,124	-3,834	2,491	-8,724	1,056
	Equal variances not assumed			-1,556	873,434	,120	-3,834	2,464	-8,671	1,002
Median SFT	Equal variances assumed	22,452	,000	1,829	874	,068	1737,844	950,018	-126,738	3602,427
	Equal variances not assumed			1,958	470,801	,051	1737,844	887,398	-5,907	3481,596

Figure: Independent samples t-test: phase 1 vs. phase 5

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	,832	,362	-,283	934	,777	-,877	3,101	-6,963	5,208
	Equal variances not assumed			-,283	932,843	,777	-,877	3,101	-6,963	5,208
SOT	Equal variances assumed	,326	,568	-,203	934	,839	-107,909	532,196	-1152,347	936,529
	Equal variances not assumed			-,203	894,750	,839	-107,909	532,196	-1152,407	936,588
Median SOT	Equal variances assumed	11,357	,001	-2,045	934	,041	-16,519	8,077	-32,371	-,668
	Equal variances not assumed			-2,045	657,344	,041	-16,519	8,077	-32,380	-,659
Glances	Equal variances assumed	,338	,561	-1,438	934	,151	-2,929	2,036	-6,924	1,067
	Equal variances not assumed			-1,438	933,792	,151	-2,929	2,036	-6,924	1,067
Median SFT	Equal variances assumed	8,258	,004	3,075	934	,002	6595,407	2144,708	2386,403	10804,412
	Equal variances not assumed			3,075	652,129	,002	6595,407	2144,708	2384,041	10806,774

Figure: Independent samples t-test: phase 2 vs. phase 4

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	,673	,412	-1,198	874	,231	-3,859	3,221	-10,180	2,463
	Equal variances not assumed			-1,201	864,466	,230	-3,859	3,214	-10,166	2,449
SOT	Equal variances assumed	1,547	,214	1,758	874	,079	868,184	493,790	-100,968	1837,337
	Equal variances not assumed			1,756	854,108	,079	868,184	494,304	-102,009	1838,378
Median SOT	Equal variances assumed	33,687	,000	-3,043	874	,002	-51,651	16,975	-84,969	-18,334
	Equal variances not assumed			-2,856	436,596	,004	-51,651	18,082	-87,191	-16,112
Glances	Equal variances assumed	1,223	,269	-2,254	874	,024	-4,907	2,177	-9,180	-,635
	Equal variances not assumed			-2,242	834,679	,025	-4,907	2,189	-9,204	-,611
Median SFT	Equal variances assumed	20,249	,000	1,221	874	,222	1162,881	952,163	-705,913	3031,675
	Equal variances not assumed			1,307	470,784	,192	1162,881	889,400	-584,805	2910,567

Figure: Independent samples t-test: phase 2 vs. phase 5

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	,046	,830	-1,320	874	,187	-4,184	3,169	-10,403	2,036
	Equal variances not assumed			-1,320	858,344	,187	-4,184	3,168	-10,402	2,035
SOT	Equal variances assumed	,227	,634	1,139	874	,255	563,346	494,395	-406,994	1533,686
	Equal variances not assumed			1,138	854,694	,255	563,346	494,831	-407,881	1534,573
Median SOT	Equal variances assumed	34,648	,000	-2,850	874	,004	-48,201	16,915	-81,401	-15,002
	Equal variances not assumed			-2,673	432,032	,008	-48,201	18,033	-83,645	-12,757
Glances	Equal variances assumed	1,081	,299	-1,864	874	,063	-3,993	2,143	-8,199	,212
	Equal variances not assumed			-1,849	822,971	,065	-3,993	2,159	-8,232	,245
Median SFT	Equal variances assumed	16,781	,000	-1,279	874	,201	-1237,004	967,418	-3135,738	661,731
	Equal variances not assumed			-1,369	470,666	,172	-1237,004	903,636	-3012,665	538,657

Figure: Independent samples t-test: phase 3 vs. phase 5

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Unlocks	Equal variances assumed	,004	,953	-,944	874	,346	-2,982	3,160	-9,184	3,220
	Equal variances not assumed			-,943	857,144	,346	-2,982	3,161	-9,185	3,222
SOT	Equal variances assumed	2,221	,136	1,748	874	,081	976,094	558,465	-119,997	2072,184
	Equal variances not assumed			1,771	870,908	,077	976,094	551,052	-105,452	2057,639
Median SOT	Equal variances assumed	15,374	,000	-1,915	874	,056	-35,132	18,350	-71,147	,883
	Equal variances not assumed			-1,828	543,812	,068	-35,132	19,217	-72,881	2,617
Glances	Equal variances assumed	,328	,567	-,902	874	,367	-1,979	2,193	-6,284	2,326
	Equal variances not assumed			-,898	839,615	,369	-1,979	2,203	-6,303	2,345
Median SFT	Equal variances assumed	24,993	,000	-2,597	874	,010	-5432,526	2091,874	-9538,209	-1326,844
	Equal variances not assumed			-2,781	467,782	,006	-5432,526	1953,235	-9270,726	-1594,326

Figure: Independent samples t-test: phase 4 vs. phase 5

Appendix 5: Research design

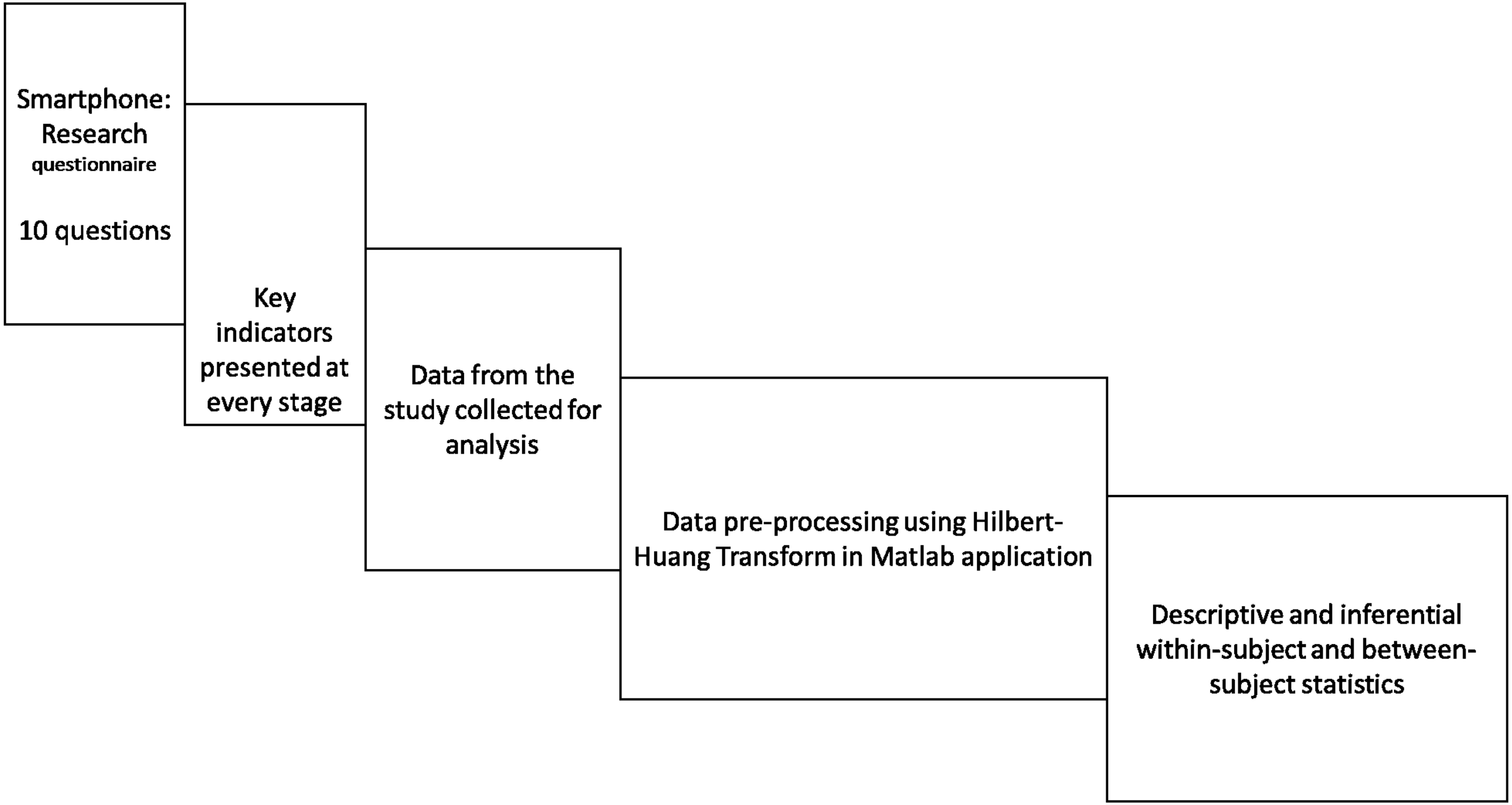


Figure: Research design