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HABITUAL SMARTPHONE USE EXPLAINING EXCESSIVE AND PROBLEMATIC USE OF SMARTPHONES AND NEGATIVE CONSEQUENCES

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ABSTRACT

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Smartphones have become rapidly ubiquitous over the last two decades and they are now necessities in people's lives. As a result, people today use smartphones more than ever before. Along with many undeniable benefits of smartphones, several unintended non-beneficial effects have been arising, yet the underlying causes and conceptualization of these effects are still widely overlooked. This study explores the dark side of smartphone use and focuses on the unintended adverse effects that smartphone use might have. Drawing from habit formation theories, dual-process theories, and technostress literature this study proposed a theoretical framework and built a research model to investigate the underlying causes of problematic behaviors and negative consequences in the context of smartphone use. An online survey among 114 regular smartphone users in Finland was conducted to empirically test and validate the research model. The results suggest that people develop strong smartphone related habits which can be used to explain increased use of smartphones and excessive smartphone use. Further, excessive use of smartphones was found to be a strong determinant of cognitive-emotional preoccupation with using smartphones which in turn significantly contributed to the formation of strain and privacy concerns as negative consequences. Also, some evidence was found that cognitive-behavioral control can dampen the effects of cognitive-emotional preoccupation on the negative consequences. In conclusion, this study showed that regular smartphone users are prone develop problematic behavioral, cognitive and emotional patterns related to smartphone use which can adversely affect their overall well-being by inducing negative consequences such as strain due exhaustion. These findings suggest that problematic smartphone use shares similar features with other more established problematic behaviors. This study also demonstrated that theoretical perspectives explaining unplanned, unintentional and irrational behaviors can be used to explore problematic behaviors in information technology (IT) use. The findings of this study contribute to the research on dark side of IT use, offer several practical implications and present opportunities for future research.

Keywords: smartphone use, excessive use, habit, technostress, strain

TIIVISTELMÄ

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Älypuhelimien käyttötottumukset selittämässä älypuhelimien liiallista ja ongelmallista käyttöä sekä negatiivisia seurauksia
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Älypuhelimet ovat yleistyneet nopeasti viimeisten kahden vuosikymmenen aikana ja ne ovat nykyään välttämättömiä ihmisten arjessa. Tämän johdosta ihmiset käytättävät älypuhelimia nyt enemmän kuin koskaan ennen. Älypuhelimet ovat tuoneet lukuisia kiistattomia etuja ihmisten elämään, mutta näiden etujen ohella esiin on noussut myös epäsuotuisia vaikutuksia, joiden syistä, muodostumisesta tai seurauksista ei ole vielä paljoa tietoa. Tämä tutkimus keskittyi tutkimaan älypuhelimien käytön epäsuotuisia vaikutuksia. Tässä tutkimuksessa muodostettiin teoreettinen viitekehys hyödyntämällä tapojen muodostumisen teorioita, kaksoisprosessiteorioita sekä teknostressikirjallisuutta ja luotiin teoreettinen tutkimusmalli selvittämään ongelmallisen älypuhelimien käytön taustalla olevia syitä sekä mahdollisia älypuhelimien käytön negatiivisia seurauksia. Tutkimusmallin testaamista ja hyväksymistä varten järjestettiin verkkokysely, johon osallistui 114 älypuhelimien käyttäjää Suomesta. Tämän tutkimuksen tulokset osoittivat, että ihmisille muodostuu vahvoja tapoja älypuhelimien käyttöön, mikä selittää älypuhelimien käytön lisääntymistä sekä sitä miksi ihmiset kokevat käyttävänsä älypuhelimia liikaa. Lisäksi älypuhelimien liiallisen käytön havaittiin myötävaikuttavan älypuhelimien käyttöön liittyvien häiritsevien ja pakkomielteisten ajatusten muodostumista, jotka puolestaan osoittautuivat vaikuttavan merkittävästi rasitteiden ja yksityisyyshuolien muodostumiseen negatiivisina älypuhelimien käytön seurauksina. Tuloksien mukaan älypuhelimien käyttöön liittyvien häiritsevien ja pakkomielteisten ajatusten vaikutus negatiivisiin seurauksiin on heikompi niillä, jotka ovat motivoituneempia ja kykenevämpiä hillitsemään ja kontrolloimaan älypuhelimien käyttöään. Yhteenvetona tutkimus osoitti, että ihmisille muodostuu helposti ongelmallisia käyttäytymis- ja ajattelumalleja älypuhelimien käyttöön liittyen, joilla voi olla haitallisia seurauksia. Nämä löydökset viittaavat siihen, että ongelmallisella älypuhelimien käytöllä on samanlaisia piirteitä muiden vakiintuneiden ongelmallisten käyttäytymisten kanssa. Tämä tutkimus myös osoitti, että ongelmallista informaatioteknologian käyttöä voidaan selittää teoreettisilla viitekehyksillä, jotka selittävät irrationaalisia ja epäjohdonmukaisia käyttäytymismalleja. Tämä tutkimus lisäsi tietämystä teknologian pimeästä puolesta, tarjosi useita neuvoja käytäntöön ja osoitti mahdollisuuksia tulevaisuuden tutkimuksille.

Asiasanat: älypuhelimien käyttö, liiallinen käyttö, tapa, teknostressi, rasitus

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1 INTRODUCTION

19th-century American philosopher and psychologist William James claimed that "ninety-nine hundredths or, possibly, nine hundred and ninety-nine thousandths of our activity is purely automatic and habitual, from our rising in the morning to our lying down each night." (James, 1899, pp. 65-66). This is a very extreme claim about the influence of habit on human life but viewing habitual behavior in the context of smartphone use in the modern world might give us a better understanding of how we use these technologies. For many, smartphones are the first thing to look at in the morning when waking up and the last thing to check in the evening before going to bed. In this study smartphone use is suggested to be based on habitual behavior that can be seen everywhere in all over the world. Various statistics of smartphone use around the world show that an average person spends around 3 to 4 hours on a smartphone every day (CodeComputerLove, 2019; He, 2019; MacKay, 2019). Furthermore, the top 20 percent of smartphone users spend 4 hours and 30 minutes looking at their phone every day (MacKay, 2019). To put these statistics into a different scale, an average person spends roughly 50 days continuously using a smartphone in a year. On average this time accumulates from 58 distinct usage sessions a day, from which 70 percent last less than two minutes and 50 percent start within 3 minutes of the previous one (MacKay, 2019). Often a behavior to this extent would be without a doubt described as problematic, compulsive, and addiction like behavior (Lee, Chang, Lin & Cheng, 2014; Oulasvirta, Rattenbury, Ma & Raita, 2012).

The proliferation of smartphones has developed relatively abruptly and topics on problematic smartphone use have become increasingly important as the effects of it have started to emerge. It is estimated that there were 3.9 billion smartphones globally in 2016, and that number is expected to rise to 6.8 billion by 2022 (Ericsson, 2017). Research has also started to recognize the negative consequences of problematic information technology (IT) use and a recent research area, often referred as the dark side of IT, has been growing in recent years (D'Arcy, Gupta, Tarafdar & Turel, 2014). Many of the studies in this research area have viewed the Internet as the main cause for technology addiction and problematic behavioral outcomes (De-Sola Gutiérrez, Rodríguez de Fonseca & Rubio, 2016). However, as smartphones have advanced rapidly to a point where they now offer a powerful computing platform with numerous compelling interactions, including Web browsers, they too have been recognized as a potential source of addictive behavior (Lin et al., 2015; Barnes, Pressey & Scornavacca, 2019). Although topics on smartphone use have become important, relatively little research has been focusing on the consequences of problematic smartphone use and especially studies that explore the underlying processes that lead to the formation of negative consequences are still rare to date (Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). Also, the cognitive and behavioral aspects in the context of problematic smartphone use have been neglected in the prior literature, which calls for further research on this phenomenon (Zheng & Lee, 2016). Due to the scarcity of theory driven studies scholars have adopted various terms and definitions to address the phenomenon of problematic IT use, which has led to inconsistency in the field (Turel, Serenko, & Giles, 2011; Zheng & Lee, 2016). Thus, more research is warranted to establish a common consensus of the conceptualizations in problematic IT use (Zheng & Lee, 2016).

Information systems (IS) researchers have a long tradition in using planned behavior and behavioral intention models as theoretical lenses to examine IS use behaviors (Carter, Clements, Tatcher & George, 2011; Turel & Qahri-Saremi, 2016). Prior IS research has mainly focused on finding out how to engage individuals using technology more and the primary way to evaluate whether a particular technology is successful has been to estimate how extensively that technology is being used (Mason & Mitroff, 1973). Thus, research on IS usage behaviors has been trying to understand concepts like technology acceptance, adoption, and continued use in the organizational context in order to make mandatory information systems more engaging and used in work environments (Bhattacherjee, 2001; Davis, Bagozzi, & Warshaw, 1989; Moore & Benbasat, 1991). The research in this area has largely based on theories that explain intentional behavior such as theories of reasoned action planned behavior (Ajzen, 1991; Ajzen & Fishbein, 1975; Bhattacherjee, 2001). These theories rely on the assumption that IT usage is mostly planned and intentional. Problematic smartphone use, however, seems to be largely irrational behavior. People might for example consciously check messages on their smartphones while driving although they acknowledge that it is risky and dangerous not only to their life but others' lives too (Basacik, Reed & Robbins, 2012; Turel & Bechara, 2016). People might use smartphones also in work and school environments and neglect their duties to spend more time on their smartphones even though they know that it can create school and work difficulties in their life (Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). This type of smartphone behavior that is potentially harmful and socially exceptionable is akin to other established problematic behaviors such as excessive alcohol consumption, gambling, and overeating (Hollander, Poskar & Gerard, 2012; Lopez-Fernandez, Honrubia-Serrano, Freixa-Blanxart & Gibson, 2014; Turel & Qahri-Saremi, 2016). Thus, theoretical lenses that are based on planned behaviors and reasoning may not be able to explain problematic smartphone use, because of their underlying assumption of rationality.

Although, this study focuses strictly on smartphone use, the scope of this study extends beyond smartphone use to all types of voluntary technology use. Voluntary technology use often takes place in personal settings, outside the organizational context, and can be often described as automatic and non-rational impulsive behavior (Clements, 2015). Research that does not account for unplanned and impulsive behavior may overstate the relationship between intention and actual behavior (Chiu, Hsu, Lai, & Chang, 2012). Consequently, growing number of IS researchers suggest that instead of using theories of planned behavior and reasoned action, theories and models that describe unplanned behaviors and unreasoned actions as well as irrational and problematic behaviors should be considered as more appropriate theoretical lenses for explaining voluntary technology use (Chan, Cheung, & Lee, 2017; Chung, Koo, & Kim, 2014; Lopez-Fernandez et al., 2014; Ortiz de Guinea & Markus 2009; Turel & Qahri-Saremi, 2016). Also, understanding the underpinning factors that drive technology engagement of voluntary technologies in personal settings has not yet been fully understood (Ang, 2017). This study aims to augment the understanding of what leads to excessive and problematic smartphone use and further to negative consequences by expanding the focus of IS research from planned behavior theories and models to theories that describe irrational and problematic behaviors.

Probably partly because of the assumption of rationality in IS use, prior literature on IS use has mainly assumed that technology use is a positive phenomenon, and that technology use is always a desirable positive outcome (Turel et al., 2011). Behaviors related to IT usage such as user engagement (Charlton & Birkett 1995), continued use (Bhattacherjee, 2001), acceptance (Davis et al., 1989) and adoption (Moore & Benbasat, 1991) of technologies have been recurring interests in the prior studies and therefore in practice too. Thus, the direction of development has been guided by those interests and IT artifact designers and developers have been focusing on understanding the key drivers for technology use. For example, the Guardian’s Simon Parkin (2018) reported that technology developers use persuasive-technology to build habitual behavior in smartphone users by rewarding them for repeating the same actions over and over again. Similarly, Facebook’s founding president Sean Parker has explained how Facebook’s architects take advantage of vulnerability in human psychology to get users consume as much time and attention to Facebook use as possible (Parkin, 2018).

Hence, smartphones today can enable and facilitate a number of compelling interactions that can be described as problematic by nature. Smartphone use behaviors such as compulsive Instagram and TikTok use, compulsive gaming and gambling can develop into uncontrollable impulsive behaviors and eventually drive high levels of smartphone use. High levels of uncontrolled impulsive technology usage can further develop into excessive and compulsive usage that can lead to more serious negative consequences (e.g., Caplan & High, 2006; Lee et al., 2014; Oulasvirta et al., 2012; Zheng & Lee, 2016). Understanding negative consequences from IT use and the behavioral patterns that cause them is essential in order to prevent and mitigate them. The responsibility to identify these negative consequences of IT use and solve the problems and risks related to them is at the IS researchers and IT designers (Lee, 2016). Hence, more research is warranted to further explore the development of problematic behaviors regarding IT use. Further, the increasingly central role of smartphones in people's lives motivates this research to enrich the existing literature on the problematic use of smartphones.

1.1 Research problem

This study contributes to the research on the dark side of IT use by explaining the drivers and consequences of excessive and problematic smartphone use. Tarafdar, Gupta and Turel (2015, p. 161) define the dark side of IT use as "a broad collection of 'negative' phenomena that are associated with the use of IT, and that have the potential to infringe the well-being of individuals, organizations and societies". The research on the dark side of IT has been focusing especially to IT-usage-related stress, work overload, interruptions, addiction, and misuse (D'Arcy et al., 2014). Smartphone use significantly contributes to this phenomenon of the dark side of IT (e.g., Cao, Masoon, Luqman, & Ali, 2018; Barnes et al., 2019; Lee et al., 2014; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). Especially, problematic smartphone use can cause stress in users (Lee et al., 2014; Zheng & Lee, 2016). Generally, the experiences of stress when using technologies is called technostress which is one of the main topics in the research on the dark side of IT (Ayyagari, Grover & Purvis, 2011; Ragu-Nathan, Tarafdar, Ragu-Nathan, & Tu 2008). Based on the presented research background, this study focuses on investigating the addressed research gaps in problematic smartphone use and its negative consequences by asking the following research questions:

1. Why are people using smartphones excessively?
2. What are the negative consequences of excessive smartphone use?
3. How does smartphone use lead to problematic smartphone use and negative consequences?

To answer these questions, this study draws its theoretical framework from habit formation theory, dual-process theories, and technostress literature. This theoretical framework is then used to develop and empirically test a theoretical model exploring the sequential process of problematic smartphone use in which habitual smartphone behavior turns into excessive use and cognitive-emotional preoccupation with using smartphones which ultimately leads to negative consequences. Problematic smartphone use can occur in various places and situations such as while in class, at work, driving or talking face to face with other people (Turel & Qahri-Saremi, 2016). Rather than trying to identify problematic smartphone related behaviors in specific instances, this study aims to identify the underlying causes of these behaviors. The negative consequences in this study are conceptualized as privacy concerns and strain due technostress from using smartphones. The concept of privacy concerns has been identified as a problem of modern technologies (Cao et al., 2018; Krasnova, Spiekermann, Koroleva & Hildebrand, 2010). Technostress in turn, is one of the most significant negative outcomes identified by the research on dark side of IT use (D'Arcy et al., 2014; Zheng & Lee, 2016).

This study also investigates how much people typically use smartphones. Prior studies examining smartphone use behaviors, especially problematic smartphone use, have mainly depended on participants' self-reported data (Cao et al., 2018; Clements & Boyle, 2018; Soror, Hammer, Steelman, Davis & Limayem, 2015; Van Deursen, Bolle, Hegner & Kommers, 2015). However, prior studies on smartphone use behaviors have also demonstrated that smartphone users tend to underestimate their actual smartphone usage on account of time distortion, making self-report data regarding smartphone use unreliable (Boase & Ling, 2013; Lin et al., 2015). Researchers have acknowledged the disadvantages of self-reported data regarding smartphone use and encouraged future research on smartphone use behaviors to track users' smartphone usage with a tracking software (Lee et al., 2014; Soror et al., 2015: Oulasvirta et al., 2012). Therefore, this study gathered smartphone usage data, namely screen time and use frequency, from built-in tracking software in participants' smartphones. This enabled the current study to obtain a better understanding of the extent to which smartphones are being used today in the modern world.

It is also important to note that, this study does not try to distinguish dependence on smartphones from dependence to smartphones (Griffiths, 2000). As such, this study attempts to explain problematic smartphone behaviors whether smartphone is being used as a medium to fuel other problematic behaviors (e.g., problematic use of social networking sites), or whether the smartphone itself is the cause for the problematic behaviors. This will enable a broad general applicability of this study.

Furthermore, many studies examining problematic use of smartphones have tried to identify the different types of smartphone use that promote problematic behaviors with diverging results (e.g., Elhai, Hall, Levine & Drovrak, 2017a; Elhai, Levine, Dvorak & Hall, 2017b; Lopez-Fernandez et al., 2014; Zhitomirsky-Geffet & Blau, 2016). For example, Elhai et al. (2017a; 2017b) showed in their studies that smartphone usage that involves more non-social feature engagement such as reading news articles and blogs, watching videos or playing games is more strongly associated with problematic smartphone use than smartphone use that involves more social feature engagement. However, the reasons why non-social smartphone use was more strongly associated with problematic smartphone use remained unclear Elhai et al. (2017b). On the other hand, many studies have had diverging results suggesting that problematic smartphone use is more related to social use of smartphones such as using Facebook and other social networking services (Lopez-Fernandez et al., 2014; Zhitomirsky-Geffet & Blau, 2016). For example, Lopez-Fernandez et al. (2014) found that people with smartphone addiction use smartphones mostly for social purposes. However, it is important to note that social-related and non-social usages of smartphones can be difficult if not impossible to completely separate from each other (Elhai et al., 2017b). Therefore, the different types of smartphone use are not distinguished from each other in this study.

2 HABITUAL SMARTPHONE BEHAVIOR

Theoretical backgrounds of habitual behaviors and habit formation are discussed next in this section. First, general definitions and concepts are discussed from cognitive psychology. Then, prior research of habitual behavior in the context of smartphone use is reviewed.

2.1 Habits

Research on human behavior has shown that substantial amounts of people's everyday acts are repeated behaviors that occur in the same context as before (Wood, Quinn & Kashy, 2002). Such behaviors can be described as habitual behaviors as habits are formed when certain acts are repeated in certain circumstances (Woody & Neal, 2007). William James first addressed the subject of habits from a scientific perspective in 1980 when he wrote a treatise titled The Principles of Psychology (1980). James (1980) wrote about habits stating that "…any sequence of mental action which has been frequently repeated tends to perpetuate itself; so that we find ourselves automatically prompted to think, feel, or do what we have been before accustomed to think, feel, or do, under like circumstances, without any consciously formed purpose, or anticipation of results." (James, 1980, p. 112). In the mid-twentieth century researchers started to emphasize purposive and cognitive perspectives to explain habits as information-processing mechanisms that are guided by the pursuit of goals (Miller, Galanter & Pribram, 1960; Wood & Rünger, 2016). In modern cognitive psychology these opposing conceptualizations are integrated. It is agreed that habit formation is closely intertwined with goal pursuit but there is also a growing consensus on that fully formed habits are viewed as automatic behaviors or responses that are triggered by situational or contextual cues such as places, other people, tasks, and emotional states (Carden & Wood, 2018; Morsella, Bargh & Gollwitzer, 2008; Oulasvirta et al., 2012; Verplanken & Aarts, 1999; Verplanken & Orbell, 2003; Woody & Neal, 2007; Wood & Rünger, 2016).

Thus, many authors have described habits similarly in recent years. Verplanken & Aarts (1999, p. 104) described habits as "learned sequences of acts that have become automatic responses to specific cues" whereas Ortiz de Guinea & Markus (2009, p. 437) conceptualize habit as "a well-learned action sequence, originally intentional, that may be repeated as it was learned without conscious intention, when triggered by environmental cues". Hence, authors today view habits as automatically performed behaviors which can be enacted with little or no conscious awareness. In other words, habits can be performed automatically and effortlessly (Ouellette & Wood, 1998; Wood et al., 2002). Also, the perception of control is higher with habitual behavior compared to nonhabitual behavior (Wood et al., 2002).

These learned automatic responses, i.e., habits, are always triggered by something often referred as cues (Carden & Wood, 2018; Wood & Rünger, 2016). Once habit is formed, the perception of the associated cues automatically stimulates the mental representation of the habitual response which makes people want to engage in the associated habitual behavior (Wood & Rünger, 2016). Specific cues that trigger habits can be found everywhere. Typically, they are seen as particular contexts (Wood et al., 2002). For example, waking up in the morning typically triggers specific habits in people, such as making coffee and brushing teeth, that are associated with the context of mornings or a morning routine. Moreover, morning routine often includes several preceding actions in a sequence, which can also act as a cue for the next habit (Wood & Rünger, 2016). Further, cues can be in the physical environment and trigger habitual behaviors as people see, smell, feel or other ways sense something familiar that is associated with those behaviors. Internal states like emotions or lack of stimuli can also trigger strong habitual behaviors (Woody & Neal, 2007).

Researchers have recently focused on identifying the psychological mechanisms behind habit formation and change (Carden & Wood, 2018; Wood & Neal, 2007.) According to a theory of habit formation, habits are formed as people repeatedly act or do something in certain circumstances to pursue their goals in daily life (Carden & Wood, 2018). Doing the same thing repeatedly in a particular context will develop associations in memory between contexts (cues) and responses (Carden & Wood, 2018). Rewards are important part of this process as habits are strengthened through reward-learning mechanisms (Wood & Rünger, 2016). That is, people are more likely to repeatedly engage in behaviors that have been rewarded in the past (Wood & Neal, 2007). Similarly, stimuli that have been rewarded in the past will call more attention in the future than non-rewarded ones (Luque et al., 2017). Also, the strength of the association between context cue and response is dependent on the reward following the behavior (Wood & Rünger, 2016). At the neural level, dopamine systems are involved in the reinforcement process when people repeat responses to experience rewards repeatedly (Wood & Rünger, 2016). As people continue to repeat the same behavior in a stable context, their goals and intentions become less influential while habits become more influential (Carden & Wood, 2018; Sheeran, Godin, Conner & Germain, 2017; Wood & Neal, 2007). Once habits have developed to a point where there is a strong enough association between the cues, behaviors and responses, they are performed automatically without the mediation of goals (Wood & Neal, 2007). Furthermore, strong habits can be influenced with reward-related cues even though performing the habit does not lead to the predicted outcome of rewards anymore (Wood & Rünger, 2016; Holland, 2004). That is why people often carry out habitual behavior even when it is conflicting with their intentions and long-term goals (Wood & Rünger, 2016).

Hence, habits can cause various problems in life, yet they are extremely useful in many situations (Wood & Neal, 2007). Arguably the best-known benefits of habits are the cognitive economy and performance efficiency in the tasks people do repeatedly in their everyday life (Wood et al., 2002). Habits also free people to engage in other activities which makes multitasking possible (Wood et al., 2002; Wood & Neal, 2007). They help at learning complex skills and provide control over behavior (Wood & Neal, 2007). From the social point of view, habits can characterize people and they can be used to predict outcomes (Oulasvirta et al., 2012; Wood & Neal, 2007). However, the benefits of these behaviors, that are executed with high automaticity and low effort, come with many potential disadvantages. Habitual responses impede people's deliberate decision making and ability to purposively guide their behavior (Wood & Rünger, 2016). Habits can cause unintended problematic behavior as the automatic responses are activated by situational context cues in improper situations (Turel & Qahri-Saremi, 2016). Behaviors may also become difficult to control as the cues triggering habits can become overly strong and responding to those cues can become difficult to resist (Oulasvirta et al., 2012; Wood & Rünger, 2016). Problematic habitual behaviors are harmful as they are often motivated by immediate gratifications and they have delayed deleterious effects because the pursuit of the more self-guided long-term goals become undermined (Marlatt, Baer, Donovan & Kivlahan 1988; Oulasvirta et al., 2012). In other words, problematic habits are performed in the pursuit of short-term rewards, and they lead to long term costs (Marlatt et al., 1988).

Habit learning systems are also involved in addictions (Wood & Rünger, 2016). Addictive behavior is described as "a repetitive habit pattern", which "is often experienced subjectively as loss of control", "that increases the risk of disease and/or associated personal and social problems" (Marlatt et al., 1988, p224). In general, behaviors that turn into addictions are initially performed voluntarily and they are often associated with rewards that have a great hedonic value (Wood & Rünger, 2016). When associations between overly strong rewards, cues and behavior are formed rapidly, the habit learning systems can become hijacked by addiction and the behavior becomes compulsive (Wood & Rünger, 2016). In addiction people often feel continuous pressure to engage in the compulsive behavior while at the same time the evaluation of the outcomes and deliberate decision making becomes impaired (Wood & Rünger, 2016). For that reason, people often continue to engage in the compulsive behavior even though they no longer want to and have intentions to quit (Wood & Rünger, 2016). Although, addiction has been traditionally associated with drug consumption, more recent research has viewed various behaviors such as gambling (Griffiths, 2006), eating (Meule & Gearhardt, 2014), Internet use (Griffiths, Kuss, Pontes & Billieux, 2016), gaming (Griffiths, Kuss & King, 2012), smartphone use (Van Deursen et al., 2015), and social networking (Griffiths, Kuss & Demetrovics, 2014) as potentially addictive too (Griffiths et al., 2016). Unlike in drug-related addictions, in behavioral addictions the behavior itself can act as a reward (Griffiths et al., 2016; Van Deursen et al., 2015).

2.2 Prior research on smartphone habits

Smartphones are extremely good at producing numerous new habits, especially those related to Internet use as smartphones have web browsers and continuous Internet access (Griffiths et al., 2016; Oulasvirta et al., 2012; Van Deursen et al., 2015). Smartphones can offer several pleasurable experiences such as receiving notifications, using social networking services, watching videos, shopping, and playing games. Using smartphones for these experiences is rewarding as they make users instantly feel better (Lopez-Fernandez, 2014; LaRose, Lin & Eastin, 2003). It has been suggested that a large part of smartphone use is based on the pursuit of these rewarding experiences (Van Deursen et al., 2015). Consequently, individuals are more likely to repeat behaviors that have been rewarded in the past (Wood & Neal, 2007; Wood & Rünger, 2016). Hence, the research and theories on habitual behavior can be used to explain the extent to which smartphones are being used today. Also, prior research has suggested that problematic habitual evolvement could explain excessive and impulsive smartphone behavior (Lee at al., 2014; Oulasvirta et al., 2012; Van Deursen et al., 2015).

Due to the similar features with the Internet in general, research on Internet use behaviors is often applied to the context of smartphones use (Beranuy, Oberst, Carbonell & Chamarro, 2009; Kun & Demetrovics, 2010; Kwon et al., 2013; Zheng & Lee, 2016). Smartphones, however, differ from other devices with Internet access in that they are specifically designed to be carried around everywhere, thus making them more pervasive (Oulasvirta et al., 2012). As a result, more constant and present situational cues are associated with the use of smartphones than other IT devices (Oulasvirta et al., 2012). Smartphones have also unique factors such as their size, portability, applications, and ubiquity which have created new conditions and expectations to be reachable at any time (Ragu-Nathan et al., 2008; Cao et al., 2018).

Oulasvirta et al. (2012) examined data from three longitudinal studies of smartphone use and found that smartphone users develop so-called checking habits that are reinforced by quickly accessible informational rewards. Oulasvirta et al. (2012, p. 107) describe these checking habits as "automated behaviors where the device is quickly opened to check the standby screen or information content in a specific application". They found that impulses to check the smartphone were associated with particular context cues including emotional states and situational cues (Oulasvirta et al., 2012). For instance, feelings of boredom and lack of stimuli were found to drive users to seek gratifications from smartphones (Oulasvirta et al., 2012). Smartphone habits were also found to increase the overall usage of smartphones as users drifted to do other things with the device after the initial response to the impulse of checking the device (Oulasvirta et al., 2012). Oulasvirta et al. (2012) concluded that a considerable part of the behavior driving smartphone use is based on habits.

Van Deursen et al. (2015) compared process and social based smartphone usage and their relationship to habitual and addictive smartphone behavior. Process usage refers to non-social feature engagement, typically content-based consumption of media, such as reading news articles, watching videos and playing games (Song, Larose, Eastin & Lin, 2004; Elhai et al., 2017a). Social usage in turn, refers to using smartphones for social purposes, such as using social networking sites, messaging, and making video calls (Elhai et al., 2017a). Both process and social based smartphone usages are motivated by pleasurable rewarding experiences (Van Deursen at al., 2015; Whang, Lee & Chang, 2003). Van Deursen et al. (2015) found in their study that both process and social related smartphone use are important determinants for habitual smartphone behaviors. Furthermore, the findings of Van Deursen et al. (2015) show that habitual smartphone use contributes to the development of addictive smartphone behavior. They suggest that smartphone habits increase the chance to develop addictive behaviors as internal and external cues associated with smartphone use trigger automatic urges in which the smartphone is unintendedly unlocked to check for notifications (Van Deursen et al., 2015). Unintended behaviors caused by maladaptive habits can lead to further adverse consequences in life (Van Deursen et al., 2015). Loss of behavioral control might be ensued directly from pleasurable experiences (Song et al., 2004).

Lee et al. (2014) found that various psychological traits promote the development of problematic smartphone habits, specifically, compulsive usage of smartphones. In their study external locus of control, materialism, social interaction anxiety, and the need for touch were found to positively influence compulsive usage of smartphones (Lee et al., 2014). External locus of control refers to individuals' perception of their ability to affect the outcomes in life through their own actions (Rotter, 1966). In general, individuals with an external locus of control believe that their lives are influenced by external forces, such as fate and luck, and that events in life are not within their control (Lee et al., 2014). Especially, external locus of control and materialism were found to drive individuals to use smartphones compulsively (Lee et al., 2014). Lee et al. (2014) also argued that individuals with an external locus of control have a higher risk of developing problematic smartphone habits as they exhibit weaker sense of self-control. Lee et al. (2014) further proposed that problematic smartphone habits are similar to other compulsive behaviors such as substance abuse, credit card exploitation and Internet dependency.

The findings of Clements and Boyle (2018) confirmed that technology-enabled triggers in smartphones induce smartphone habits. They defined technology-enabled triggers as technology characteristics such as indicator lights, vibration sequences, push notifications and sounds that provide behavioral stimuli and set behaviors into motion (Clements & Boyle, 2018). They concluded that, the more cues and triggers are designed into smartphones and applications the more likely users will develop habits with using them (Clements & Boyle, 2018). Furthermore, technology habit was also found to be an important contributor to compulsive smartphone use (Clements & Boyle, 2018). They defined compulsive use as "spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient" (Clements & Boyle, 2018, p. 35). Finally, technology complexity in smartphone applications was found to negatively influence smartphone habits indicating that the more complex a particular technology is, the less likely people will develop habits with using that technology (Clements & Boyle, 2018).

Tarafdar, Maier, Laumer and Weitzel (2020) proposed and empirically evidenced that habits drive individuals to use social networking sites as a coping mechanism to stress caused by the use of social networking sites itself. Further, their findings indicate that habitual use of social networking sites strengthens the relationship between stress from the use social networking sites and addiction to using social networking sites (Tarafdar et al., 2020). These findings can be extended to the context of smartphone use (Tarafdar et al., 2020).

Finally, habitual behavior has often been viewed as an important part of Internet and other digital addictions where individuals often repetitively engage in behavioral patterns to relieve pain or escape from reality (Oulasvirta et al., 2012; Van Deursen et al., 2015). Lack of self-control and self-regulation have also been associated with habits and addictive behavior regarding Internet and smartphone use (Caplan & High, 2006; Turel & Qahri-Saremi, 2016; Van Deursen et al., 2015). The habitual use of smartphones is also driven by the fear of missing out as individuals use smartphones to reduce social pressures by checking smartphone to not miss out on events or updates (Elhai et al., 2017b).

To conclude, smartphones enable quick and easy access to rewards and instant gratifications which drives users to check smartphones repetitively (Oulasvirta et al., 2012). Research on smartphone habits has also indicated that habitual use of smartphone can be an antecedent of impulsive and problematic behavior (Lee et al., 2014; Oulasvirta et al., 2012; Van Deursen et al., 2015). Smartphone habits can cause unintended behavior as internal and external cues activate automatic urges which are difficult to control (Van Deursen et al., 2015).

3 PROBLEMATIC SMARTPHONE USE

Problematic behaviors are typically impulsive behaviors that are considered inappropriate, prohibited, or sometimes even dangerous, and that have deleterious effects as they are often inconsistent with people's long-term goals in life (Cao et al., 2018; Festl, Scharkow & Quandt, 2013; Spada, 2014; Ture & Qahri-Saremi, 2016). A review of the literature on the problematic IT use behaviors reveals that researchers have adopted various concepts and definitions to address problematic use of IT (Spada, 2014; Tarafdar et al., 2015; Zheng & Lee, 2016). Extant literature has described problematic behaviors in the context of smartphone use with varying terms such as overuse (Boonjing & Chanvarasuth, 2017), compulsive use (Lee et al., 2014), impulsive use (Turel & Qahri-Saremi, 2016), excessive use (Cao et al., 2018; Zheng & Lee, 2016), prohibited use (Billieux, Van der Linden & Rochat, 2008), dangerous use (Billieux et al., 2008); disadvantageous use (Turel & Qahri-Saremi, 2016), and addiction (Van Deursen et al., 2015; Barnes et al., 2019). While these terms capture different dimensions of problematic smartphone use, using various definitions vaguely can lead to confusion when results are interpreted inconsistently (Spada, 2014; Zheng & Lee, 2016). For example, problematic smartphone use has been often conceptualized fully as behavioral addiction, but recent research has suggested that not all problematic smartphone use meet the key features of an addictive behavior such as loss of control, tolerance, and withdrawal (Barnes et al., 2019; Billieux, Maurage, Lopez-Fernandez, Kuss & Griffith, 2015; Turel & Qahri-Saremi, 2016). Also, behaviors can be problematic even when they are performed for the first time or only once (Turel & Qahri-Saremi, 2016). Using smartphones while driving, for instance, can be undoubtedly seen as problematic but it can occur without the presence of an addiction. Problematic behaviors might also be performed repetitively but they still are not necessarily addiction like behaviors as using smartphones repetitively while driving can just be a bad habit and thus not produce the negative symptoms of addiction such as those from withdrawal and tolerance (Billieux et al., 2015; Turel & Qahri-Saremi, 2016). However, problematic behaviors can often be derived from behavioral addictions (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). In the current study the definition for problematic use of smartphones is adapted from Turel and Qahri-Saremi (2016, p. 1088) as "unplanned, typically impulsive" smartphone use instances that "are less advantageous to users, as they can likely lead to negative consequences for the user and are often disapproved by the society". Further, rather than trying to identify problematic smartphone related behaviors in specific instances, this study attempts to identify the underlying causes that indicate the presence of problematic smartphone use behaviors overall.

Research on IT use behaviors has often followed the same theoretical paradigm where technology users are assumed to be rational beings and that their decisions regarding technology use are based on a rational reasoning, intention and planning (Ajzen, 1991; Bhattacherjee, 2001; Fishbein & Ajzen, 1975; Steelman & Soror, 2017; Turel & Qahri-Saremi, 2018). Problematic smartphone use, however, is arguably irrational and unplanned rather than rational and planned behavior. This is evident as people use smartphones excessively in school and work environments even though they acknowledge that it is probably disadvantageous to their long-term goals (Zheng & Lee, 2016; Turel & Qahri-Saremi, 2016). People use smartphones also while driving although they know that it is not only dangerous but also illegal (Basacik et al., 2012). Therefore, the often-used theoretical frameworks of IT use behaviors might not be appropriate in examining problematic smartphone use, given their underlying premise of rationality (Steelman & Soror, 2017; Turel & Qahri-Saremi, 2016). Due to the similarities with other well-established problematic behaviors, such as problematic drinking and gambling, recent research on problematic IT use has adopted theoretical lenses that have been previously used to describe other irrational and impulsive problematic behaviors (Cao et al., 2018; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016).

One recently adopted theoretical lens that has been used to examine the underlying causes of problematic use of social networking services on smartphones is based on dual-process (or dual-system) theories of decision making and judgement (Cao et al., 2018; Evans, 2008; Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). These theories explain that problematic behaviors stem form a decision-making deficit and outline the mechanisms that are involved when people make decision whether to act on impulsions or to engage in deliberate information processing to control impulsions (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). These mechanisms can be broadly depicted as two types of processes or systems in the human brain: those that involve impulsive, fast, automatic, or unconscious processes (System 1 or Type 1 processes) and those that include slow, effortful, and conscious processes (System 2 or Type 2 processes) (Evans, 2008; Wood & Rünger, 2016). The type 1 processes are typically responsible for the strong persistent urges or preoccupying thoughts and feelings whereas type 2 processes are activated when humans engage in more deliberate decision making and goal pursuit (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). In this study it is proposed that these type 1 and type 2 processes can be used to explain the underlying causes of problematic use of smartphones.

3.1 Dual-process theories and problematic smartphone use

Dual-process theories have been around in cognitive and social psychology from the 1980s but has been adopted increasingly into more common use in various domains in the 21st century (Evans, 2008). Although these theories have various different implications, they all seem to have agreed on the idea that there are two distinct types of processes, often referred as System 1 and System 2 processes, that guide human behavior (Evans, 2008). System 1 processes are often described as unconscious, rapid and automatic processes with high capacity whereas System 2 processes are described as conscious, slow, and deliberative (Evans, 2008). The way the two processes perform and their roles in decision making are also generally agreed. System 1 processes provide a sort of default response to stimulant cues in different situations and circumstances whereas Systems 2 processes are activated and intervene decision making by imposing an alternative when individual is sufficiently motivated and able to do so (Evans & Stanovich 2013; Wood & Rünger, 2016). In other words, responses to stimulant cues are largely automatic unless people are motivated and capable to engage in more deliberate decision making (Wood & Rünger, 2016).

Dual-process theories have been used to explain various problematic behaviors, such as compulsive alcohol consumption, impulsive eating, gambling, smoking, and problematic use of social networking sites (Evans, 2008; Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018). In these problematic behaviors the processes in the two systems have been found to function similarly (Turel & Qahri-Saremi, 2016). Generally, system 1 processes generate strong impulsions and urge to engage in the problematic behavior when exposed to stimulant cues, while at the same time the goal-directed control provided by the system 2 processes is impaired which restricts the capacity for intentionally select alternative actions (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). As problematic IT use has been shown to have similar features with other problematic behaviors, dual-process theories have been deemed to provide appropriate theoretical lenses for explaining problematic behaviors regarding smartphone use too and, studies that have adapted this approach to explain problematic smartphone use behaviors have shown promising results (Cao et al., 2018; Soror et al., 2015; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018; Zheng & Lee, 2016). Further, by comparing dual-process theories-based models to planned behavior-based models these studies have shown that the dual-process approach can better explain impulsive and problematic behaviors associated with smartphone use than the planned behavior-based models (Cao et al., 2018; Turel & Qahri-Saremi, 2016). Specifically, the factors used in the dual-process models, namely excessive use, cognitive-emotional preoccupation and cognitive-behavioral control, have shown greater explanatory power in explaining problematic smartphone use than the factors such as perceived usefulness and satisfaction that have been often used in studies examining IT use behaviors (Cao et al., 2018; Turel & Qahri-Saremi, 2016). Hence, this study adapts the approach of the dual-process theories as theoretical lenses to examine problematic smartphone use. Also, the key factors for representing the two types of processes of decision making and judgement are conceptualized from established research dual-process research. Next, these factors will be discussed further.

3.1.1 Excessive use of smartphones

Excessive use of smartphones refers to the extent to which smartphones are used more than planned (Caplan & High, 2006). Prior studies suggest that excessive use of IT, often in the context of Internet or smartphone use, is a necessary but not sufficient condition to experience negative outcomes such as symptoms of an addiction in IT use (Caplan & High, 2006; Davis, 2001; Zheng & Lee, 2016). Excessive use of smartphones is therefore conceptualized as a so-called necessary cause of negative outcomes from smartphone use, which means that it must be present or occurred in order for the adverse outcomes to occur (Davis, 2001). It is important to note, however, that the negative outcomes are not required to occur when the necessary cause is present or has occurred (Davis, 2001). For example, individuals who use IT in their work, may not experience negative outcomes from using IT although they might spend majority of their waking hours with using IT. Therefore, excessive use of IT may not directly cause adverse consequences. Extant studies on IT use have highlighted that the way individuals think about a certain technology can explain the extent of the negative outcomes they experience associated with their use of that technology (Cao et al., 2018; Caplan & High, 2006; Haagsma, Caplan, Peters & Pieterse, 2013; King, Haagsma, Delfabbro, Gradisar & Griffiths, 2013; Zheng & Lee, 2016). In other words, if an individual thinks that his/her smartphone use is excessive and harmful for his/her well-being, actual negative consequences caused by the excessive smartphone use are more likely to occur. In this study the excessive use of smartphones is used as a factor to represent the manifestation of the impulsions and urges generated by the system 1 processes in the dual-process approach. However, in excessive use, the system 2 processes are expected to intervene and purposively guide behavior when smartphone use is perceived as conflicting with one's goals in life, for example when preparing for exams in school. Thus, excessive smartphone use might not automatically lead to negative outcomes.

Although, excessive smartphone use, such as monitoring social media excessively, is not sufficient to cause negative outcomes alone, it can adversely affect the overall well-being of individuals as it has been associated with numerous negative side effects such as difficulties to manage life, exhaustion, social problems and heightened psychological distress (Caplan & High, 2006; Chesley, 2005; Luqman, Cao, Ali, Masood & Yu, 2017). Prior research on problematic smartphone use has showed that excessive use of smartphones induces maladaptive cognitions (i.e., obsessive and distorted thoughts and feelings) and is therefore an important contributor in the development of problematic smartphone behavior (Cao et al., 2018; Caplan & High, 2006; Davis, 2001; Zheng & Lee, 2016). Thus, checking notifications compulsively or monitoring social media excessively may further develop into more compulsive behavior that can lead to more serious negative outcomes such as sleep disturbance, stress, social- and work related problems, physical problems, depression, addiction and other mental health problems (Bianchi & Phillips, 2005; Matusik & Mickel, 2011; Oulasvirta et al., 2012; Takao, Takahashi & Kitamura, 2009; Harmon & Mazmanian, 2013; Thomée, Eklöf, Gustafsson, Nilsson & Hagberg, 2007; Thomée, Härenstam & Hagberg, 2011; Zheng & Lee, 2016).

Compulsive smartphone use has been often used to describe problematic smartphone behaviors (e.g., Clements & Boyle, 2018; Lee et al., 2014). Generally, compulsive behavior can be described as ''a response to an uncontrollable drive or desire to obtain, use, or experience a feeling, substance, or activity that leads the individual to repetitively engage in behavior that will ultimately cause harm to the individual and/or others'' (O'Guinn and Faber, 1989, p. 148). In the context of technology use it has been described as "spontaneous interaction with technology that is unintentional, uncontrollable, effortless, and efficient" (Clements & Boyle, 2018, p. 35). It commonly involves a pattern of repetitive, impulsive non-rational behavior and has been well established in contexts like compulsive eating, gambling, and substance misuse (Parylak, Koob, & Zorrilla, 2011). Reflecting on the dual-process theories, the concept of compulsive use depicts a situation where system 1 processes exert a continuous pressure to engage in smartphone use when exposed to situational cues coupled with impaired system 2 processes that no longer can control or inhibit the behavior (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). This study, however, adopts a different set of factors to depict that situation.

In this study the factors for representing the two types of processes involved in problematic smartphone use are adapted from Collins and Lapp's (1992) manifestations of these processes which were originally used and validated in the context of problematic alcohol use. The factors representing system 1 and 2 processes in this study are cognitive-emotional preoccupation with using smartphone, and cognitive-behavioral control over using smartphone, respectively. This model has been systematically constructed and validated to be a comprehensive representation of these processes that guide human behavior in the context of various problematic behaviors (Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018). In prior studies, it has also been proven to be relevant for explaining problematic behaviors in the context of smartphone use, suggesting that problematic smartphone use shares similar neural and cognitive etiology with other well established problematic behaviors (Cao et al., 2018; Soror et al., 2015; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018).

3.1.2 Cognitive-emotional preoccupation with using smartphone

Cognitive-emotional preoccupation with using smartphone refers to obsessive and persistent thoughts, or maladaptive cognitions, associated with smartphone use (Caplan & High, 2006; Davis, 2001; Turel & Qahri-Saremi, 2016). Preoccupation with a behavior makes people want to act out the behavior, which then can lead to problematic behaviors as engaging in the behavior becomes increasingly more difficult to resist, making people act out the behaviors even when they are conflicting with intentions and have negative effects on achieving long term goals (Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). Habit formation mechanisms are central part of the development process of problematic behaviors (Wood & Rünger, 2016). Preoccupying thoughts and feelings toward a behavior are result of the habit formation processes where strong associations between behaviors, stimulant cues, and desired outcomes (i.e., rewards) are formed (Wood & Rünger, 2016). These strong urges are automatic responses generated by the system 1 processes when exposed to the associated stimulant cues (Evans, 2008; Wood & Neal, 2007; Wood & Rünger, 2016). In other words, when exposed to relevant stimulant cue (e.g., notification sound) cognitive-emotional preoccupation with smartphone use emerge as a strong urge to pick up the smartphone to check what the notification is. This behavioral pattern may lead to problematic behaviors as the impulsions become increasingly more difficult to resist even in situations where smartphone use is considered inappropriate or prohibited.

Cognitive-emotional preoccupation with using smartphones may lead into problematic smartphone use by positive and/or negative behavioral reinforcement mechanisms (Turel & Qahri-Saremi, 2016). Positive behavioral reinforcement mechanisms refer to the development of behaviors that are associated with rewarding experiences (Turel & Qahri-Saremi, 2016). Smartphones offer numerous pleasurable and engaging experiences, such as winning games and receiving messages, that function as a reward and increase the change to develop problematic behaviors (Van Deursen et al., 2015). Negative behavioral reinforcement mechanisms in turn refer to the development of behaviors that are performed in order to avoid or alleviate negative feelings, such as loneliness, boredom and distress (Oulasvirta et al., 2012; Turel & Qahri-Saremi, 2016). Smartphones provide quick and effortless way to avoid and escape negative feelings by offering pleasurable experiences which make users instantly feel better (Oulasvirta et al., 2012; Van Deursen et al., 2015). As these behavioral patterns are repeated, negative feelings can become strong stimulant cues that automatically trigger strong urges to check smartphone in order to avoid those negative feelings which increase the change to develop problematic behaviors (Oulasvirta et al., 2012; Van Deursen et al., 2015). To conclude, cognitive-emotional preoccupation with using smartphones is deemed an appropriate manifestation of the system 1 processes that drive users to develop problematic behaviors regarding smartphone use (Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018).

3.1.3 Cognitive-behavioral control over using smartphone

Cognitive and behavioral control refers to people's motivation and capabilities to engage in deliberate decision making and goal pursuit (Wood & Rünger, 2016). It can involve identifying and evaluating desired and adverse outcomes, setting and initiating behavioral intentions as well as inhibiting, interrupting or changing actions (Gollwitzer & Brandstätter 1997; Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). When an individual is motivated and capable, cognitive-emotional control is activated by the system 2 processes to intervene and guide behavior towards more favorable outcomes and goals (Evans, 2008; Wood & Rünger, 2016). Prior studies have shown that lack of cognitive-emotional control is an important contributor to problematic smartphone use (Cao et al., 2018; Turel & Qahri-Saremi, 2016; Wilmer & Chein, 2016). Prior studies on smartphone use suggest that smartphone users are often unaware, unmotivated or unable to control their smartphone use which increases the chance to develop problematic behaviors regarding smartphone use (Oulasvirta et al., 2011; Turel & Qahri-Saremi, 2016; Wilmer & Chein, 2016). Impulsive smartphone behavior, such as frequent checking, is suggested to be more strongly driven by uncontrolled impulses rather than reward seeking (Wilmer & Chein, 2016). Hence, cognitive-emotional control is presumably an appropriate representation of the system 2 processes in the dual-processes approach of problematic smartphone use.

4 STRESS DERIVED FROM SMARTPHONE USE

The term stress has a long history, and it has been used widely not only in different fields of research but also in everyday life situations in various contexts. Thus, the definition of stress might differ in different branches of science and situations. However, the word "stress" as it is commonly known today can be originated to Hans Selye who is sometimes referred as the father of stress research or the founder of stress theory (Petticrew & Lee, 2011). Selye diagnosed stress as "the nonspecific response of the body to any demand made upon it" (Selye, 1976, p. 137). This approach views stress as a physiological response to stressors, where the stressors are typically defined as changes in the environment that are challenging, threatening or demanding. Diseases and natural disasters are examples of such changes in the environment that cause stress. As Selye (1956; 1976) considered stress to be merely a physiological response to changes in the environment, his approach did not take the differences between individuals or their experiences into consideration (Lazarus & Folkman, 1984). Therefore, according to Selye's approach, all changes in the environment (stressors) that cause stress are automatically and equally stressful to all individuals, despite their individual differences (Lazarus & Folkman, 1984). Later, researchers argued Selye's definition of stress to be inadequate and advanced the definition of stress to consider individual differences such as personalities, emotions and biological construction as important contributors to the experiences of stress (Lazarus & Folkman, 1984).

The transactional theory of stress and coping (Lazarus 1966; Lazarus & Folkman, 1984) explains stress as more dynamic process between individual and his/her environment. In the transactional theory, stress is viewed as a transactional process between people and environment (Lazarus & Folkman, 1984). In this approach, stress is formed when people find the demands of the environment exceeding their capabilities to cope with the demands and thereby threatening their well-being (Cooper, Dewe & O'Driscoll, 2001; Lazarus, 1990). Unlike in Selye's (1956, 1976) approach, this model suggests that stress is a subjective rather than objective phenomenon and that the process of stress is based on the people’s perceptions or appraisals of the stress creating demands in the environment (Lazarus & Folkman 1984).

In the extant stress literature, there seems to be a consensus that the transactional approach is the appropriate theoretical lens to view stress, especially in organizational context and in technology use (Cooper et al., 2001; Lazarus, 1966; Lazarus & Folkman, 1984; Ragu-Nathan et al., 2008). Ragu-Nathan et al. (2008) displayed the transactional approach in a theoretical model of technostress that comprises the four main components of the approach in an organizational context. The components in the model are stressors, situational factors, strain and other organizational outcomes. In figure 1 the model is adapted to the context of smartphone use. Stressors are defined as such events, demands, stimuli, or condition that cause stress for an individual when encountered in the environment (Cartwright & Cooper, 1997; Ragu-Nathan et al., 2008). Situational factors are mechanisms that can reduce the effects of stress (Ragu-Nathan et al., 2008). In the context of organizations and work environment situational factors include mechanisms such as social support or job redesign (Ragu-Nathan et al., 2008). Strains are the negative consequences of stress caused by stressors and they are typically behavioral, psychological, and physiological symptoms (Cooper et al., 2001; Kahn & Byosiere, 1992; Ragu-Nathan et al., 2008). The general experience of stress itself is also sometimes referred as strain (Lazarus & Folkman 1984). The other (organizational) outcomes refer to the repercussions of the individuals’ strains such as weakened work performance (Ragu-Nathan et al., 2008). For example, job dissatisfaction as an individual strain can lead to negative organizational outcomes such as absenteeism and reduced efficiency (Ragu-Nathan et al., 2008).

Majority of stress related studies on IT use are focused on the negative effects of stress such as different strains in different contexts (e.g., Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Salo, Pirkkalainen & Koskelainen, 2019). However, it is important to note that stress can have positive impacts too. Selye (1974) distinguished the negative and positive responses to stress and coined the terms “distress” and “eustress” (Selye, 1974). Distress refers to negative, unpleasant experiences and results of stress whereas eustress is considered as the positive experiences and healthy, constructive responses and outcomes of stress (Kupriyanov & Zhdanov, 2014; Lazarus, 1974). Eustress can be, for example, the excitement that comes from starting a new job or preparing for an important meeting. One commonly adopted approach to view the relationship between eustress and distress is based on the Yerkes-Dodson Law which suggests that there is an inverted-U relationship between stress and performance (Benson & Allen, 1980; Yerkes & Dodson, 1908). As stress increases, performance and efficiency increase too, but only up to a point and if stress levels continue to increase too high, performance and efficiency decrease (Benson & Allen, 1980). In short, stress is initially a positive phenomenon, but too much stress results in distress.

4.1 Technostress

The spread of mobile information technology has brought many benefits and enabled people to do things that were not possible before. Smartphones can complete many things that were not imaginable even for room sized supercomputers few decades ago. Today's smartphones enable users to make video calls, interact on social networking services, watch videos, play games and even do most of the work-related tasks that previously required an office desk setup. However, along with all these advancements some unintended negative effects have been identified to emerge. One such negative effect that has been shown to have a significant impact on people's life is technostress (Fischer & Riedl, 2017). In the current study, technostress refers to the experiences of stress from the use of IT, specifically from the use of smartphones (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). This broad conceptualization covers a large portion of the overall stress people experience in the modern world as pervasive IT, such as smartphones, have become an integral part of peoples' everyday lives. There are over three billion people using smartphones in the world and the number is expected to keep on growing in the following years (O'Dea, 2021). Research examining and identifying these negative effects and consequences of the usage and spread of IT is called the dark side of IT and technostress is one of the main topics in this research area (Tarafdar et al., 2015).

Technostress research integrates stress and IS literature. Originally technostress was defined by Brod (1984, p. 16) as ''a modern disease of adaptation caused by an inability to cope with the new computer technologies in a healthy manner''. Already from this first definition of technostress the transactional interpretation of stress can be seen; new computer technologies cause stress because they are perceived as demands in the environment that exceed the individual's resources and thereby endanger his/her wellbeing (Cooper et al., 2001; Lazarus, 1966; Lazarus & Folkman, 1984). At first, technostress research focused mainly on IT use in organizational and work environments (e.g., Ayyagari et al., 2011; Brillhart, 2004; Ragu-Nathan et al., 2008; Sethi, King & Quick, 2004; Tarafdar, Tu & Ragu-Nathan, 2010; Weil & Rosen, 1999). Studies on work related technostress has shown that work related IT can cause technostress in employees which then can have various negative consequences on the individual and organizational level (Ayyagari et al., 2011; Ragu-Nathan et al., 2008; Srivastava, Chandra & Shirish, 2015). Recently, research on technostress has expanded outside the organizational context as voluntary technology use in other contexts has grown at an exponential rate (Cao et al., 2018; Lee et al., 2014; Maier, Laumer, Weinert & Weitzel, 2015; Salo et al., 2019). Recent research has contributed to the evolving body of literature on technostress and adopted a broader conceptualization of technostress as the experiences of stress from the use of IT which is often associated with the information and communication overload due to IT use (Ragu-Nathan et al., 2008; Tarafdar, Cooper & Stich, 2019).

This study draws from the technostress framework of Ragu-Nathan et al. (2008) and Ayyagari et al. (2011) and adapts a model that depicts the technostress formation process in the context of problematic smartphone use (see figure 1). Ragu-Nathan et al. (2008) identified five different aspects or dimensions of technostress in the organizational context that impact employees in various ways by creating demanding conditions that can be difficult to cope with. Ayyagari et al. (2011) theorized that certain IT characteristics in the organizational environment contribute to the formation of technostress creators (stressors), which subsequently can adversely affect employees' well-being and eventually affect work and organizational outcomes. Various studies have advanced the notion of technostress by adapting the theoretical framework of Ragu-Nathan et al. (2008) and Ayyagari et al. (2011) to various contexts outside the organizational context, including problematic smartphone use (Cao et al., 2018; Lee et al., 2016; Salo et al., 2019; Zheng & Lee, 2016).

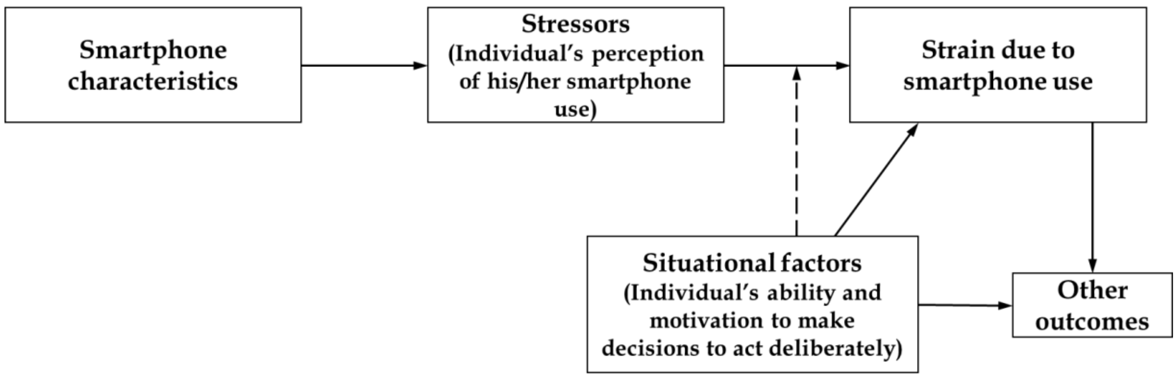

FIGURE 1 Technostress framework in the context of problematic smartphone use (adapted from Ayyagari et al., 2011; Ragu-Nathan et al., 2008).

4.1.1 Technostress creators

Technostress is caused by technostress creators, which generally are IT-related stressors such as specific technology features, characteristics or conditions that are perceived as demanding (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). Individuals' adverse psychological responses or other reactions and outcomes in relation to these techno-stressors are called strains (Ayyagari et al., 2011). Ayyagari et al. (2011) suggest that certain technology characteristics such as constantly updating features, complexity and intrusiveness induce various stressors which eventually lead to strain (Ayyagari et al., 2011). This overall transaction process between individuals and technologies that leads to strain is broadly referred to as technostress (Ayyagari et al., 2011; Cooper et al., 2001; Tarafdar et al., 2015; Tarafdar et al., 2010).

Ragu-Nathan et al (2008) developed and empirically validated five different dimensions of technostress that generate stress-creating conditions which further contribute to the formation of strain. These dimensions are techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty, and they have been shown to cause overarching conditions that create stress in various contexts, including smartphone use (Cao et al., 2018; Lee et al., 2014; Ragu-Nathan et al., 2008).

In the organizational context techno-overload refers to a situation where different technologies create demands for employees to work faster and more productively which cause the employees to feel pressured and overwhelmed (Ragu-Nathan et al., 2008). Having to use multiple different technologies simultaneously can be perceived as taxing and exceeding available resources and thereby resulting to the formation of stress (Ragu-Nathan et al., 2008). Ayyagari et al. (2011) proposed that certain technology characteristics like perceived usefulness, complexity, reliability, pace of change and presenteeism are related to the formation of the techno-overload stressor because they increase the workload and expectations of productivity. For example, employees might get job requests via email that leads them doing additional work tasks that they had not planned to do (Barley, Meyerson & Grodal, 2011).

Techno-invasion depicts the invasive aspect of technology that comes from the intrusive features and characteristics of technology (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). These intrusive features are often associated with presenteeism and low anonymity as they create conditions where individuals feel that they have to be constantly connected and available (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). In the organizational context the invasiveness and presenteeism of technology is seen in situations where technology enables employees to be reachable at anytime and anywhere which then restrain them from disengaging from work demands outside of work (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). The findings of Ayyagari et al. (2011) suggest that constant connectivity enabled by IT increases the workload by enhancing the speed of workflow and expectations of productivity. Constant connectivity also increases the employees' uncertainty about the expectations towards them as it can create conflicting demands when new tasks can come up any time (Ayyagari et al., 2011). Constant connectivity also enables interruptions at work, encroaches on the personal space of individuals and makes people feel that they always working (Ayyagari et al., 2011).

Techno-complexity refers to situations where the use of technology is perceived as difficult and challenging and therefore stressful (Ragu-Nathan et al., 2008). As individuals appraise their abilities being inadequate to the demands of technology, any tasks related to the use of that technology can be perceived as demanding (Ragu-Nathan et al., 2008; Lazarus & Folkman, 1984). This requires individuals to expend more time and effort in learning and understanding these technologies and their features. Also, as the expectations are not clear, the individuals may end up seeking information from various different places as they try to keep up with perceived expectations, which can lead to exhaustion (Ragu-Nathan et al., 2008; Tarafdar et al., 2010). Information flood as well as the inability to identify relevant information can lead to dissatisfaction towards IT and other unfavorable outcomes (Tarafdar et al., 2010). Constant changes in technologies, such as new advancements, improvements and features, can lead to frustration as the demands to learn more accumulates to an overwhelming level (Ayyagari et al., 2011; Ragu-Nathan et al., 2008).

Techno-insecurity refers to the individual's perception of the threat of losing his/her job due to technological advancements or to people with better understanding of new technologies (Ragu-Nathan et al., 2008). As new technologies are introduced and new skilled workers enter the field, older employees may feel the threat of losing their job if they are unable to keep up with new technologies. Especially constant changes in technologies have a significant impact on job insecurity (Ayyagari et al., 2011). In the context of smartphone use techno-insecurity could be seen in phenomena such as fear of missing out where individuals feel being threatened to miss out on important things if they don't keep up with important information (Elhai et al., 2017b).

Finally, the techno-uncertainty aspect of technostress refers to the ambiguity between expectations of the technological environment and individual's abilities such as skills and knowledge (Ragu-Nathan et al., 2008). Continuing changes in technologies (e.g., upgrades) may concern users which creates pressure to constantly study and learn new things to keep up with the technological developments (Ragu-Nathan et al., 2008). Furthermore, the pace of change makes the knowledge to become rapidly obsolete, which leads to situation where individuals become stressed as they are unable to develop a base of experience for particular technologies (Tarafdar et al., 2010).

It is important to note that these dimensions can impact each other, and the experienced stress can originate from a mixture of various stress-creating conditions. For example, constant connectivity that is enabled by IT increases the workload because employees are expected to work faster and more efficiently (Ayyagari et al., 2011). In other words, the invasive effect of technologies is contributing to the formation of technostress together with the techno-overload aspect.

4.1.2 Technostress and smartphone use

Research have found numerous characteristics particular to smartphone use, such as constant connectivity, flood of push notifications and privacy concerns, that can become overwhelming stressors and exceed user's resources to cope with them (Boonjing & Chanvarasuth, 2017; Cao et al., 2018; Lee et al., 2014; Oulasvirta et al., 2012; Salo et al., 2019). Smartphones have unique features that make them more persuasive than other technologies. The most significant feature particular to smartphones is that they are relatively small handheld devices that are designed to be carried around. Because of this, smartphone users are exposed to much more constant and present situational cues than with other technologies (Oulasvirta et al., 2012). Smartphones can intrude people's life at any given time with lights, tones, and vibrations, distracting people from current tasks to engage with the device instead. Even if these distracting features in the device itself are turned off, internal and external cues such as preoccupying thoughts and feelings guide our behavior to engage with the device. Also, the smartphone itself can often be the cue that makes people to pick it up and engage with it (Wilmer & Chein, 2016). Constant disruptions while focusing on important tasks can be annoying and provoke anxiety and stress (Oulasvirta et al., 2012; Salo et al., 2019; Van Deursen et al., 2015). Furthermore, smartphone users can experience an invasion of privacy as they feel that they are expected to be available at any time and that they have to adjust their behavior to these new conditions established by smartphones (Cao et al., 2018; Ragu-Nathan et al., 2008;). Hence, drawing from Ragu-Nathan et al. (2008) it is proposed in this study that smartphone use can lead to strain as people feel that their life is being invaded by smartphones.

Another particular feature to smartphones is that they offer a wide variety of channels to instantly access information and to connect to other people (Oulasvirta et al., 2012). This can be initially rewarding but it can quickly become exhausting as users feel that they cannot keep up with the overwhelming amount of continuously renewing information (Oulasvirta et al., 2011; Salo et al., 2019). For instance, Salo et al. (2019) proposed that the flood of push notifications and real-time information renewability expose smartphone users to become overly dependent on and overloaded by their smartphones which further contributes to concentration and sleep problems. Hence, drawing from Ragu-Nathan et al. (2008), smartphone use is proposed to contribute to the formation of the techno-overload stressor which is further proposed to lead to experiences of exhaustion as a strain due to smartphone use. Feeling exhausted from using IT is an individual's psychological reaction to stressors and is commonly called techno-exhaustion in the extant technostress literature (Ayyagari et al., 2011; Cao et al., 2018; Maier et al., 2015).

The issue of privacy has become increasingly more important aspect of smartphones and smartphone applications such as social networking sites (Bright, Kleiser & Grau, 2015; Krasnova et al., 2010). In general, privacy risks have become a problem of modern technologies (Bright et al., 2015; Cao et al., 2018; Krasnova et al., 2010; Salo et al., 2019). Smartphones and smartphone applications often collect personal information from their users and there have been concerns about what different service providers do with the collected information (Bright et al., 2015; Salo et al., 2019). Also, transparent interaction between users and websites has been shown to raise concerns about privacy online (Bright et al., 2015; Krasnova et al., 2010). Bright et al. (2015) found that majority of social media users in their study had privacy concerns and that privacy concerns were positively related to experiences of social media fatigue. Salo et al. (2019) had similar findings indicating that privacy and security uncontrollability with social networking sites can become a stressor and further contribute to the formation of strain. Cao et al. (2018) showed in their study that excessive use and cognitive-emotional preoccupation with social networking induced experiences of privacy invasion as a strain which further diminished the academic performance of students. Hence, privacy concerns are proposed to be a possible negative consequence of smartphone use.

To conclude, problematic smartphone use can induce various stressors that cause technostress and contribute to the formation of strain and other adverse consequences. In general, higher levels of compulsive usage have been found to lead to higher levels of technostress regarding smartphone (Lee et al., 2014). Thus, it is suggested in this study that an individual, who thinks that his/her smartphone use is excessive and have preoccupying thoughts and feelings about smartphone use is likely to experience strain and privacy concerns as negative consequences of problematic smartphone use.

5 HYPOTHESES AND RESEARHC MODEL DEVELOPMENT

In this section, the multidisciplinary theoretical framework is encapsulated into a series of hypotheses related to smartphone habits, problematic smartphone use and negative consequences of smartphone use. The proposed hypotheses are derived from appropriate theoretical literature. Finally, the proposed theoretical research model is introduced.

5.1 Habitual smartphone behavior

Smartphones can enable and facilitate a number of compelling interactions and therefore have the potential to produce strong habits. An example of a common and strong habit for smartphone users is so-called checking habit, where smartphone is checked several times during a day even though there is no specific reason for checking it (Oulasvirta et al., 2012). This behavior can be explained by the informational rewards that are instantly available in smartphones (Oulasvirta et al., 2012). Rewarding experiences are at the core of habitual behaviors as humans are prone to repeat the actions that have previously resulted in desirable outcomes (Luque et al., 2017). These kinds of automatic responses are triggered by external and internal cues such as places, events, and emotional states (Oulasvirta et al., 2012). Smartphones are particularly good at producing various cues for users as they have numerous built-in features such as sounds, lights, flashes, vibrations, and notification indicators that provide behavioral stimuli and set behaviors into motion (Clements & Boyle, 2018). These kinds of technology-enabled triggers have been shown to be important contributor to technology related habits (Clements & Boyle, 2018). Subsequently, the stronger the habits are the more often and easier those habits are triggered by the associated cues (LaRose & Eastin, 2004). Thus, it is hypothesized that habitual smartphone use increases the extent to which smartphones are being used in terms of screen time accumulation and use frequency. Hence, the following hypotheses are proposed:

> H1a: Habitual smartphone use leads to increased smartphone use in terms increased screen time.
>
> H1b: Habitual smartphone use leads to increased smartphone use in terms of increased use frequency.

Research on smartphone habits has further shown that habitual use of smartphones can induce impulsive and excessive smartphone behaviors (Clements & Boyle, 2018; Lee et al., 2014; Oulasvirta et al., 2012; Van Deursen et al., 2015). Smartphone use can be described to be excessive when smartphones are used longer times than planned (Caplan & High, 2006). People arguably do not plan on using smartphones several hours per day and checking them repetitively throughout the day. Furthermore, habitual smartphone use has been suggested to contribute to the development of addictive smartphone behavior (Van Deursen et al., 2015). Technology related addictive-like behaviors such as overuse due to loss of self-control can be referred as problematic technology use (Oulasvirta et al., 2012; Turel et al., 2011; Turel & Qahri-Saremi, 2016). However, not all problematic behaviors meet the criteria of addictive behavior (Barnes et al., 2019; Turel & Qahri-Saremi, 2016). As habit learning mechanisms are involved in the development of problematic behaviors, it is proposed that smartphone habits contribute to the development of problematic smartphone behaviors (Oulasvirta et al., 2012; Wood & Rünger, 2016). In this study, cognitive-emotional preoccupation with using smartphones (i.e., obsessive and persistent thoughts about using smartphones) is proposed to be the root cause of problematic smartphone use. Hence, it is proposed in the current study that habitual smartphone use is positively associated with excessive use of smartphones and cognitive-emotional preoccupation with using smartphones:

> H1c. Habitual smartphone use positively influences excessive use of smartphones.
>
> H1d. Habitual smartphone use positively influences cognitive-emotional preoccupation with using smartphones.

5.2 Increased use of smartphones

Studies have shown clear evidence that increased use of smartphones can create more technostress and other negative consequences such as physical and psychological symptoms (Boonjing & Chanvarasuth, 2017). Also, as people use increasingly more smartphones, it is reasonable to expect that they are more likely to think that their smartphone use is excessive. Similarly, as the level of smartphone use increases it is expected that people will develop more stronger and consistent associations between learned behavioral patterns and relevant stimuli regarding smartphone use. Consequently, more persistent and stronger urges that are increasingly more difficult to resist are expected to emerge when smartphone users are exposed to associated stimulant cues more often. Thus, the increased use of smartphones is hypothesized to be positively associated to the excessive use of smartphones, cognitive-emotional preoccupation with using smartphones and negative consequences from smartphone use such as strain and privacy concerns. The following hypotheses are proposed:

> H2a. Smartphone screen time is positively related to the excessive use of smartphones.
>
> H2b. Smartphone screen time is positively related to cognitive-emotional preoccupation with using smartphones.
>
> H2c. Smartphone screen time is positively related to strain due to smartphone use.
>
> H2d. Smartphone screen time is positively related to privacy concerns.
>
> H3a. Smartphone use frequency is positively related to excessive use of smartphones.
>
> H3b. Smartphone use frequency is positively related to cognitive-emotional preoccupation with using smartphones.
>
> H3c. Smartphone use frequency is positively related to strain due to smartphone use.
>
> H3d. Smartphone use frequency is positively related to privacy concerns.

5.3 Problematic smartphone use

Behavioral studies suggest that cognitive, emotional and behavioral mechanisms and processes are involved in the formation of negative outcomes associated with problematic IT use (Barnes et al., 2019; Davis, 2001; Turel & Qahri-Saremi, 2016). In these studies, individual's cognitions (or thoughts) are emphasized as the main cause for problematic behaviors and the negative outcomes of those behavior. Dual-process theories of decision making and judgement suggest that maladaptive cognitions such as obsessive thoughts, distorted thought process are the root cause of problematic behaviors regarding technology use (Cao et al., 2018; Davis, 2001; Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). In this study, cognitive-emotional preoccupation with smartphone use portrays these maladaptive cognitions which can be described as obsessive and persistent thoughts about using smartphones (Davis, 2001; Turel & Qahri-Saremi, 2016). These cognitions often emerge as automatic cognitive and/or emotional responses to specific internal and/or external stimuli (cues). People often carry out these responses, despite the possible detrimental consequences (Turel & Qahri-Saremi, 2016; Wood & Rünger, 2016). For example, the thought of using Facebook can be associated with the pleasurable feeling that comes when somebody gives a like to a photo. As this behavioral schema with rewarding experiences is repeated, strong urges to use Facebook can be triggered later on by various cues such as notifications and feelings like loneliness or boredom. These urges become increasingly more difficult to resist as the rewarded behavior is repeated more often (Turel & Qahri-Saremi, 2016).

Excessive use of smartphones is a necessary condition to experience negative outcomes from problematic smartphone use (Caplan & High, 2006; Zheng & Lee, 2016). Prior studies provide evidence that excessive smartphone use is a strong predictor of cognitive-emotional preoccupation with using smartphones in various contexts such as social networking, Internet use and smartphone checking (Cao et al., 2018; Oulasvirta et al., 2012; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). Excessive smartphone use is often viewed as one of the main reasons to cause maladaptive cognitions regarding smartphone use (Cao et al., 2018; Zheng & Lee, 2016). Thus, it is hypothesized that:

> H4. The excessive use of smartphones is positively related to cognitive-emotional preoccupation with using smartphones.

5.4 Negative consequences

Prior studies have shown that cognitive-emotional preoccupation with using IT can cause problematic behaviors use and adverse consequences (Cao et al., 2018; Davis, 2001; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). Prior research suggest that the way individuals think about their use of technologies can be an important factor in explaining the extent of the negative consequences experienced from the use of those technologies (Caplan & High, 2006; Haagsma et al., 2013). Therefore, excessive users might experience negative consequences from using smartphones although it might not be a sufficient condition to cause them alone (Caplan & High, 2006).

Problematic behaviors can drive high levels of unplanned smartphone use and cause unintended behaviors that can interfere with other acts in daily life (Oulasvirta et al., 2012; Van Deursen et al., 2015). Smartphone users can experience strong urges to check smartphones even in situations where it is inappropriate or even illegal to use smartphones, for example while driving a car, listening to class lectures or attending meetings (Turell & Qahri-Saremi, 2016). Prior studies suggest that both excessive use of smartphones and cognitive-emotional preoccupation can lead to various adverse outcomes such as difficulties to manage life, exhaustion, social problems and heightened psychological distress, sleep disturbance, stress, social- and work-related problems, physical problems and mental health problems (Caplan & High, 2006; Chesley, 2005; Bianchi & Phillips, 2005; Elhai et al., 2017b; Harmon & Mazmanian, 2013; Luqman et al., 2017; Matusik & Mickel, 2011; Oulasvirta et al., 2012; Takao et al., 2009; Thomée et al., 2007; Thomée et al., 2011; Zheng & Lee, 2016).

This study focuses on strain caused by stressors related to smartphone use as the negative consequence of problematic smartphone use. The experience of stress from using technologies is called technostress in the IS literature (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). As smartphones have become ubiquitous, people can feel that they are expected to have smartphones with them all the time and everywhere (Van Deursen et al., 2015). People often live up to these expectations as they avoid making undesired impression to others, which can make them use more smartphones (Caplan, 2007). The expectation to be reachable at anytime and anywhere can create a stress-creating condition called life invasion (or techno-invasion), in which individuals feel that their personal lives are being invaded by mobile technologies (Ayyagari et al., 2011; Tarafdar, Tu, Ragu-Nathan & Ragu-Nathan, 2007; Ragu-Nathan et al., 2008). Consequently, smartphone users can feel exhausted as smartphones generate and facilitate these stress-creating conditions. Psychological reaction where individual feels exhausted from using IT is called techno-exhaustion and it is a specific from of psychological strain (Ayyagari et al., 2011; Tarafdar et al., 2010). This study proposes that these two conditions, namely life invasion and techno-exhaustion, can create stress-creating demands and further generate strain due to the specific characteristics of smartphones such as small size and constant connectivity.

The proliferation of smartphones has also brought other types of unintended consequences such as privacy risks which can create concerns and anxiety for smartphone users (Cao et al., 2018; Krasnova et al., 2010). Prior studies have associated privacy concerns regarding IT use with excessive use and cognitive-emotional preoccupation with using social media (Cao et al., 2018), social media fatigue (Bright et al., 2015), ubiquitous connectivity (Cao et al., 2018), helpfulness, self-efficacy, and confidence (Logan, Bright & Grau, 2018). The common understanding is that transparent interaction between users and IT services, such as websites, creates concerns about privacy (Bright et al., 2015; Karahasanovic et al., 2009; Krasnova et al., 2010).

It is proposed in this study that excessive use of smartphones as well as cognitive-emotional preoccupation with using smartphones are positively related to the formation of strain and privacy concerns due to smartphone use. Thus, the following hypotheses are proposed:

> H5a. Excessive use of smartphones is positively related to strain due to smartphone use.
>
> H5b. Excessive use of smartphones is positively related to privacy concerns.
>
> H6a. Cognitive-emotional preoccupation with using smartphones is positively related to strain due to smartphone use.
>
> H6b. Cognitive-emotional preoccupation with using smartphones is positively related to privacy concerns.

To summarize, it is proposed that problematic smartphone use and the negative consequences from smartphone use are developed as a sequential process in which smartphone habits lead to increased use of smartphones which further contributes to the development of problematic cognitive, emotional and behavioral patterns with smartphone use and eventually lead to negative consequences (see figure 2). Figure 3 shows the proposed main research model and hypotheses. Definitions of the main constructs are summarized in table 1.

FIGURE 2 Theorized sequential development process of problematic smartphone use and negative consequences

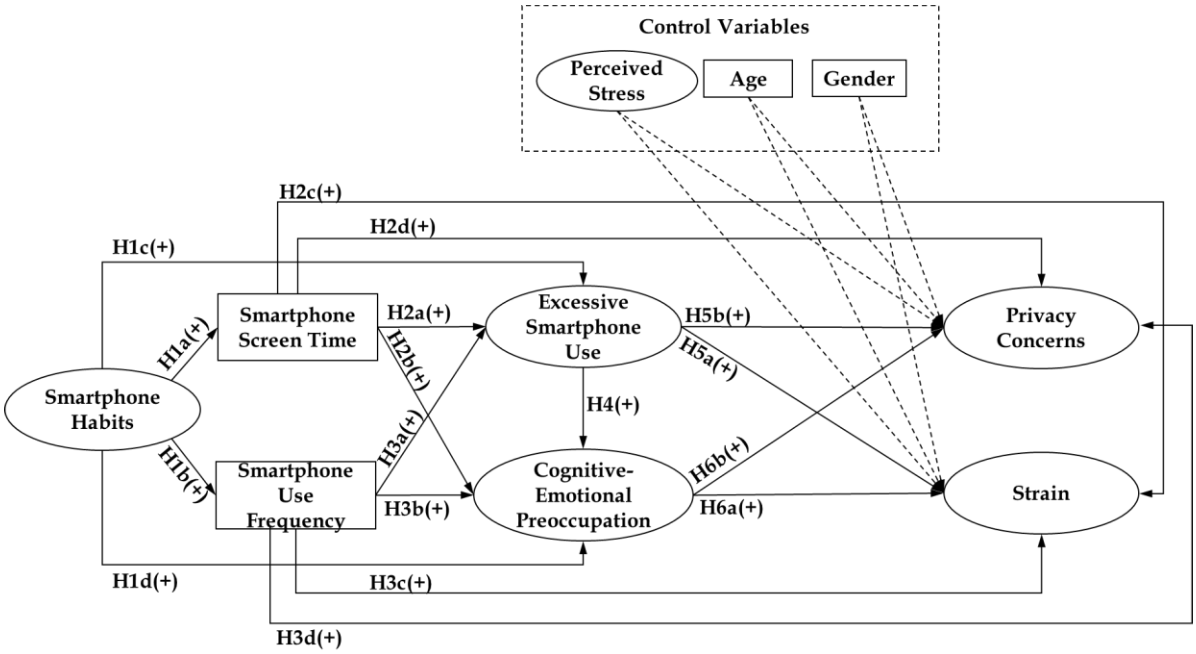

FIGURE 3 Main research model and proposed hypotheses

5.5 The moderating effects of cognitive-behavioral control

Cognitive-behavioral control refers to one's ability and motivation to engage in deliberate decision making to guide behaviors towards long term goals in life. In this study cognitive-behavioral control represent specifically smartphone users' motivation and ability to inhibit and resist the urges to use smartphone repetitively and the ability to interrupt or change impulsive thoughts and behaviors in order to engage in more deliberate goal pursuit such as studying for exams. Prior research on problematic behaviors suggest that cognitive-behavioral control can moderate effect on the relationship between cognitive-emotional preoccupation with a behavior and the negative consequences of that behavior (Cao et al., 2018; Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016). Individuals who are motivated and able to restrict their problematic behaviors can develop a strong cognitive-behavioral control over the behavior, which has a mitigating effect on the recurrence of that behavior (Collins & Lapp, 1992). People with strong cognitive-behavioral control are less disturbed and tempted by impulsions and are more likely to be able to override them, which eventually reduces the frequency and strength of the persistent distracting thoughts and behaviors (Cao et al., 2018; Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016).

Prior studies have provided support for this moderating effect of cognitive-behavioral control in the context of smartphone as well. Turel and Qahri-Saremi (2016) examined problematic social media use among students and concluded that students with strong cognitive-emotional preoccupation and low cognitive-behavioral control have a higher risk to develop problematic behaviors with

Facebook use, which subsequently resulted in diminished academic performance. Cao et al. (2018) had similar results providing support for the moderation effect of cognitive-behavioral control in problematic smartphone use. Their results indicated that cognitive-emotional preoccupation does not lead to adverse outcomes, such as exhaustion, life invasion and privacy invasion, in individuals with strong control over their mobile social media application use (Cao et al., 2018). Thus, it is reasonable to expect that cognitive-behavioral control over using smartphones can dampen the relationships between cognitive-emotional preoccupation with using smartphones and the negative consequences of problematic smartphone use (see figure 4). Hence, the following hypotheses are proposed:

> H7a. Cognitive-behavioral control over smartphone use dampens the positive relationship between cognitive-emotional preoccupation with using smartphones and privacy concerns.

> H7b. Cognitive-behavioral control over smartphone use dampens the positive relationship between cognitive-emotional preoccupation with using smartphones and strain due to smartphone use.

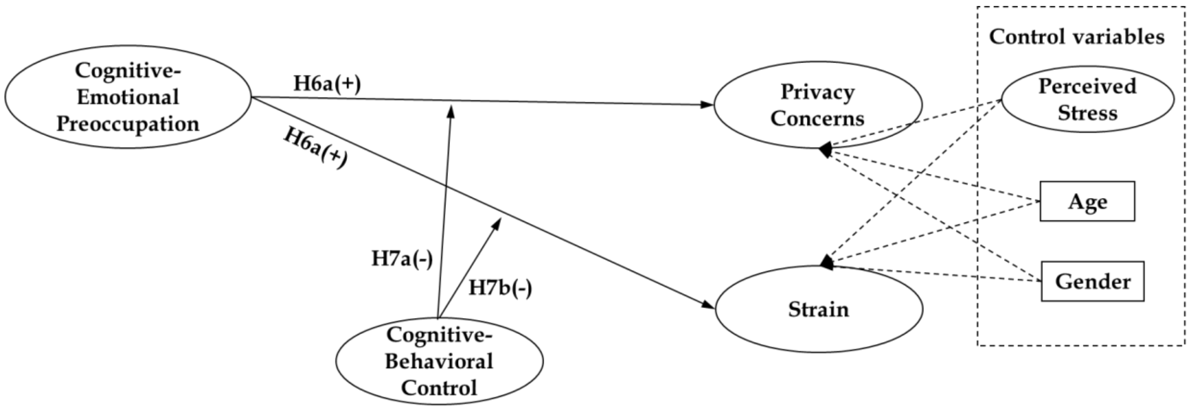

FIGURE 4 Model of the moderating effect of cognitive-behavioral control

TABLE 1 Definitions of the main constructs

Construct	Definition	Reference
Smartphone Habit	"Learned sequences of acts that have become automatic responses to specific cues".	(Verplanken & Aarts, 1999, p. 104)
Excessive Smartphone Use	The extent to which smartphone use is longer than the time planned.	(Caplan & High, 2006; Zheng & Lee, 2016; Cao et al., 2018)
Cognitive-Emotional Preoccupation	Maladaptive cognitions or obsessions and persistent thoughts about smartphone use.	(Davis, 2001; Collins & Lapp, 1992; Turel & Qahri- Saremi, 2016)
Emotional Preoccupation	Internal stimulant cues such as negative emotions that generate strong urges to use smartphones.	(Turel & Qahri-Saremi, 2016)
Cognitive Preoccupation	Persistent distracting thoughts about using smartphones that generate strong urges to use smartphones.	(Caplan & High, 2006; Turel & Qahri-Saremi, 2016; Haagsma et al., 2013)
Cognitive-Behavioral Control	Motivation and capability to inhibit, control and change impulsive thoughts and behaviors and engage in deliberate decision making.	(Collins & Lapp, 1992; Turel & Qahri- Saremi, 2016; Cao et al., 2018)
Strain	Individual's behavioral, psychological, or physiological responses to stress-creating conditions or stressors (e.g., exhaustion).	(Cooper et al., 2001; Ayyagari et al., 2011; Ragu-Nathan et al., 2008)
Techno-Exhaustion	Feelings of exhaustion due to smartphone use (a specific form of psychological strain).	(Cao et al., 2018; Maier, 2015; Maier et al., 2015; Zheng & Lee, 2016; Ayyagari et al., 2011)
Life Invasion	Negative perception that the smartphone has invaded personal life and has an too central role in life.	(Cao et al., 2018; Ragu-Nathan et al., 2008; Tarafdar et al., 2007)
Privacy Concerns	Concerns about compromised privacy due to inability to control personal information on smartphones and applications.	(Ayyagari et al., 2011; Cao et al., 2018; Bright et al., 2015; Karahasanovic et al., 2009; Salo et al., 2019)

6 METHODOLOGY

The selected research methods for the empirical part of this study are discussed in this section. First, reasoning for quantitative research and data collection methods are discussed. Then, utilized measurement items and the data collection procedure are presented in further detail.

6.1 Quantitative research

The typically used qualitative and quantitative research methods in IS research can be employed to investigate the phenomena of the dark side of IT. Since the emphasis in this study was on developing causal relationships, a quantitative approach was chosen for this study. Also, one main goal of this study was to capture a realistic picture of the extent to which smartphones are being used today. Therefore, reliable methods to capture smartphone usage levels was essential for this study. Self-reporting methods, such as interviewing subjects, are unreliable in measuring the extent of smartphone use as prior studies have demonstrated that smartphone users tend to underestimate their actual smartphone usage (Andrews, Ellis, Shaw & Piwek, 2015; Boase & Ling, 2013; Lin et al., 2015). Therefore, a quantitative approach where the data for smartphone use were collected straight from the subjects' smartphones was considered as an appropriate approach for this study. The empirical data were collected through questionnaire survey methodology. The collected statistical data were then analyzed using multivariate statistical techniques. Confirmatory factor analysis (CFA) was used to validate the measurement model and structural equation modeling (SEM) method was utilized to analyze the structural causal model and the causal relationships in it.

A common way to examine people's habits in IT use is to examine repetitive behaviors from quantitative data. Prior studies of smartphone use have compared averages of behaviors or applications uses (Lin et al., 2015; Oulasvirta et al., 2012; Verkasalo, 2009). In this study, smartphone use frequency and screen time were chosen for the measures to capture smartphone use behaviors and the extent to which smartphones are used on a daily basis.

6.2 Measures

The constructs for the research model were adopted from existing literature and each construct were measured by using multiple measurement items that have been shown to be valid and reliable in prior studies. All items were assessed on a 7 or 5-point Likert type scales from “strongly disagree” to “strongly agree” or from “never” to “always”. Respondents were asked to mark the appropriate number to indicate the extent to which they agreed or disagreed with each statement.

The measures for habitual smartphone behavior were adapted from the Self-Report Habit Index (SRHI) (Verplanken & Orbell, 2003) as well as from studies that have used validated measures to capture habitual behavior in the context of technology use before (Limayem, Hirt & Cheung, 2007; Tarafdar et al., 2020; Van Deursen et al., 2015). In these studies, habitual behavior is considered as an automatic response to certain internal or external cues. Limayem et al. (2007) used a habit scale for measuring habitual Internet use, Tarafdar et al. (2019) used similar scale to capture habits in the context of social networking use and Van Deursen et al. (2015) adapted similar habit measures to capture smartphone habits.

The scale for excessive smartphone use was adapted from the studies of Caplan and High (2006), Zheng and Lee (2016) and Cao et al. (2018) where it has been shown to be valid and reliable to scale to measure excessive use of IT. It contains three measurement items that are designed to capture user’s perception of whether his/her smartphone use is excessive.

Empirically tested and validated scales for cognitive-emotional preoccupation with using smartphones and cognitive-behavioral control over using smartphones were adapted from the studies of Collins and Lapp (1992), Turel and Qahri-Saremi (2016), Turel and Qahri-Saremi (2018) and Cao et al. (2018). These measures were originally developed for problematic drinking by Collins and Lapp (1992). Turel and Qahri-Saremi (2016) adapted them in their study to the context of problematic use of Facebook and Cao et al. (2018) in turn, adapted them to the context of excessive use of mobile social networking sites. In the current study cognitive-emotional preoccupation was operationalized as a reflective second-order factor comprised of two first-order factors, namely emotion and cognitive preoccupation, which were adapted to the context of problematic smartphone use. The factor for emotion refers to avoiding and alleviating negative emotions that drive problematic smartphone use (Turel & Qahri-Saremi, 2016). The Factor for cognitive preoccupation refers to obsessive, distorted and distracting thoughts about using smartphones (Turel & Qahri-Saremi, 2016). Cognitive-behavioral control comprised of six items that are designed to capture respondents’ level of concern about the problematic behavior as well as motivation to restrict and alter the impulsive thoughts and behaviors (Turel & Qahri-Saremi, 2016). The scale was adapted to the context of using smartphones to capture worries about smartphone use as well as plans and prior attempts to reduce, limit and inhibit it.

Three constructs, each with four items, were used to measure negative consequences caused by the stressors associated with smartphone use. These constructs are life invasion, techno-exhaustion and privacy concerns. A construct for strain was then operationalized as a reflective second-order factor comprising the first-order factors of life invasion and techno-exhaustion. The constructs for negative consequences were adapted from previous studies and modified to the context of smartphone use. Life invasion was adapted from Ragu-Nathan et al. (2008), Tarafdar et al. (2007) and Cao et al. (2018). Techno-exhaustion was adapted from Ayyagari et al. (2011), Maier et al. (2015), Steelman and Soror (2017) and Cao et al. (2018). Privacy concerns was adapted from Karahasanovic et al. (2009), Bright et al. (2015) and Cao et al. (2018).

Furthermore, a short form of perceived stress scale from Cohen, Kamarck and Mermelstein (1983) was used to measure respondents' level of perceived stress for control purposes. It is argued to be an important control in studies that use dual process theories, and it has been used in the context of problematic IT use in prior studies as well (Turel & Qahri-Saremi, 2018). Also, demographic variables, such as age and gender were captured for descriptive and control purposes.

The data for smartphone usage were collected via iPhone's, Android's and Samsung's smartphone usage tracking software that are preinstalled into most of the latest devices of these brands. Latest Android devices come with a set of Digital Wellbeing tools that track and allows users to monitor their smartphone usage. These tools include a dashboard where users can view how frequently different apps are used, how much time is spent in different apps, how many notifications the apps have send, and how many times the phone is unlocked. Similar to Android's Digital Wellbeing tools, the latest IOS devices come with a Screen Time feature that tracks smartphone usage and allows users to access real-time reports about their smartphone usage. These features were utilized to collect data from respondents' smartphone usage. Respondents were asked to check their screen time and use frequency from the period of the previous week and report it to the questionnaire. Detailed step by step instructions with screen captures were provided to help respondents check the data from different smartphones brands. Also, respondents' top three most used applications during the previous week were asked to be reported.

A Finnish version of each measure was created by utilizing a suggested translation method (Van De Vijver & Leung, 1997). First, the items were translated into Finnish with the help of a native Finnish speaker who had an academic degree in English and experience in translating English to Finnish. Then, another native Finnish speaker with an academic degree in English was asked to describe how she understood the Finnish material and how she would translate it to English. The original measures were compared to the translations, and the final Finnish translations were corrected so that they would be understood in the same way as the measures in the original language.

6.3 Sample and Data Collection

The data for this study were collected via an online questionnaire that was sent to potential smartphone users in Finland. The target subjects were individuals who own a smartphone and use it in their daily lives. As an inclusion criterion it was required that the participants had enabled the screen time feature in their smartphones and that they had screen time and use frequency data available from the period of the previous week. As the purpose of this study was to attempt to generally examine smartphone users and their relationship to smartphones, no other criteria for participants were applied. Also, prior research on problematic smartphone use suggests that a sample without purposely identifying problematic behaviors before the surveys is appropriate (Caplan, 2007; Lee et al., 2014).

Before distributing the final survey, a pilot test with a convenience sample was conducted to assess the internal consistency of the measurement items and to get feedback from the questionnaire. Based on the results and the feedback from the pilot test the questionnaire was refined accordingly. Eventually there were 41 items for eight constructs in the final survey (i.e., nine questions for smartphone habits, three questions for excessive use, seven questions for cognitive-emotional preoccupation, six questions for cognitive-behavioral control, four questions for techno-exhaustion, four questions for life invasion, four questions for privacy concerns and four questions for perceived stress). The final survey was distributed with an accompanying letter where participants were assured that their responses would be anonymous, confidential, and that the data would only be used to make statistical analyses where individual responses could not be identified. The final survey took approximately 15 minutes to complete on average.

For the final survey, potential smartphone users were invited through a link to an online questionnaire that was created using Webropol 3.0 questionnaire software. The link to the questionnaire was first distributed through the Jyväskylä University's mailing list by the university's communication specialist. The mailing list is the main information channel on program specific matters and all students of the Faculty of Information Technology are automatically added onto the mailing list when they start their studies. The link was distributed with an accompanying letter where the individuals were motivated to participate and encouraged to invite other potential subjects to participate as well. In addition to the mailing list, networks and connections to people were harnessed to distribute the link to potential subjects.

A total of 357 individuals clicked the link and opened the questionnaire, from which 132 started to fill the questionnaire and 114 respondents completed it. Thus, out of the 357 individuals who opened the questionnaire 32% completed the survey.

7 DATA ANALYSIS AND RESULTS

In this section, the utilized analysis methods and their results are first discussed and presented. First, preliminary analyses used to explore the collected data and validate the constructs in the data are discussed. Then, the results from testing the proposed hypotheses in the structural causal models are presented and discussed.

7.1 Data screening and preliminary analyses

Before testing the measurement and the research model, the initial data were screened, edited and prepared carefully in order to identify any violations of the conditions related to the further analysis of structural equation modeling. Also, several preliminary analyses were made to ensure the validity and quality of the further analyses. Screening and examination of the initial data also allows the researcher to get a better understanding of the dataset (Aminu & Shariff, 2014). In the following section, the examination and treatment procedures of missing data, unengaged responses, outliers, normality and common method bias are discussed.

7.1.1 Missing data, unengaged responses, and outliers

In quantitative research missing data is rather a rule than an exception (Vehkalahti, 2014). In this study, missing values in the data were treated with data imputation. Quantitative scientific literature suggests that in cases where there are less than 5% missing values per item, missing values should be imputed using mean (Hair, Hult, Ringle & Sarstedt 2013). The dataset had a total of 13 items with missing values, all less than 5% missing. Thus, the missing values were replaced using median for the ordinal scale variables and mean for the continuous scale variables. Also, responses with less than 80% completion could cause problems such as standard error and bias in further analyses and therefore such responses are suggested to be removed (Dong & Peng, 2013; Enders, 2003). In the current study, none of the completed responses in the dataset had missing values over 20% and therefore no responses were removed due to too high rate of missing values.

Unengaged responses were searched from the data by examining the variance within the respondents' responses to identify wrongly filled questionnaires. Since all responses had reasonable variance in the values between different items, no unengaged responses were identified.

Next, outliers were examined from the dataset. The examination of outliers is important because problematic outliers can distort statistical tests and therefore compromise the results of the later analyses (Hair, Black, Babin & Anderson 2010; Tabachnick & Fidell, 2013). A Mahalanobis Distance Test was applied to assess multivariate outliers from the data (Tabachnick & Fidell, 2013). Linear regression methods in IBM SPSS v26 were used to calculate Mahalanobis score. Then Chi-square critical value was calculated using a p value of 0,001 and the total number of items, that is 41, as the degrees of freedom. Finally, the calculated Chi-square critical value of 73,40 was used as a cut-off value for the Mahalanobis scores. Each of the Mahalanobis scores was under the calculated critical value. Thus, no cases were removed.

7.1.2 Skewness & kurtosis

After screening the data for missing values and outliers, the distribution of the data was examined. Normal distributions of the data are an important assumption for further statistical analysis (Hair et al., 2010). To assess the normality of the data a statistical method of skewness and kurtosis was applied (Hair et al., 2010; Kline, 2011). No serious deviations from normality assumptions were observed for the indicators of the latent factors nor for all the other variables in terms of skewness. One of the items (HAB3) for the habit construct was negatively skewed and had the absolute value of skewness greater than 3 which can be held as a threshold for acceptable values when using SEM (Kline, 2011; Brown, 2006). However, the indicators for the latent factors were measured on Likert scales which are ordinal in nature and therefore they are not expected to necessarily have normal distributions. The skewness value for the item HAB3 was -3,7 and it was decided to keep in the dataset.

In terms of kurtosis, four indicators for the latent factor of habit were highly kurtotic with kurtosis values over 3. Again, these indicators are measured on 7-point Likert scales and are ordinal in nature, thus not expected necessarily to be normally distributed. Two other variables, namely age and smartphone use frequency, were also highly kurtotic with kurtosis values of 5,8 and 11,2, respectively. While these do violate strict rules of normality, they are acceptable according to other authors such as Kline (2011) and Brown (2006) who argue that kurtosis values under 20 should not yet indicate serious problems. Also, the age variable was expected to be highly kurtotic since the sample population consisted mostly of university students and their circle of acquaintances. Furthermore, SEM as a statistical analysis method is fairly robust and therefore small deviations usually do not pose a concern for normality assumptions (Brown, 2006; Griffin & Steinbrecher, 2013). The items with deviations from normality assumptions were decided to keep in the dataset and they were observed carefully in the further analysis. Thus, no indicators of the latent factors or other variables were removed due to issues with the normality assumptions.

Further, the results of the confirmatory factor analysis show that all the latent factors except the factor for habit are normally distributed. The latent factor for habit is highly kurtotic with a kurtosis value of 11,8, but as stated before this should not yet indicate serious problems (Kline, 2011). The habit construct was decided to keep in the dataset and watch carefully in further analysis.

7.1.3 Descriptive characteristics

A total of 114 individuals completed the questionnaire. The mean age of the respondents was 29.8 years (SD = 6,9), ranging from 20 to 57 years. The sample included 70 females and 43 males. Within the respondents, 80,7% had achieved a bachelor’s degree/college diploma or higher. Although the sample is not a perfect representative of the Finnish populations, it is adequate to the purposes of this study. In terms of smartphone screen time accumulation and use frequency, respondents on average used their smartphones for 3 hours and 58 minutes (SD = 1 hour 55 minutes) a day and 76,1 (SD = 50,5) times a day. Screen times ranged from 9 hours 41 minutes to 15 minutes a day and use frequencies ranged from 378 to 5 times a day. The sample split evenly between iOS and Android device users as 50,9% of the respondents used an iOS device and the rest 49,1% used an Android device. The most used applications were Instagram, WhatsApp and Safari. Table 2 summarizes the demographic characteristics.

TABLE 2 Demographics of respondents

Category		**Frequency**	**Percentage (%)**
Gender	Female Male Rather not say	70 43 1	61,4 37,7 0,9
Age (years)	Less than 30 Over 30	80 34	70,2 29,8
Education (highest)	Comprehensive school Upper secondary education Bachelors' degree/College diploma Higher academic degree N/A	1 19 52 40 2	0,9 16,7 45,6 35,1 1,8
Smartphone screen time (daily average)	Less than 60 minutes 60 - 120 minutes 121 - 180 minutes 181 - 240 minutes 241 – 300 minutes 301 - 360 minutes Over 360 minutes N/A	2 11 25 27 25 7 16 1	1,8 9,6 21,9 23,7 21,9 6,1 14,0 0,9
Smartphone use frequency (daily average)	Less than 50 times 50 – 100 times 101 – 150 times Over 150 times N/A	33 52 17 7 5	28,9 45,6 14,9 6,1 4,4
Application was in the top 3 most used applications	Instagram WhatsApp Safari Chrome Facebook TikTok	53 35 23 19 17 13	46,5 30,7 20,2 16,7 14,9 11,4

7.2 Confirmatory factor analysis

Before hypotheses testing, the measurement model should be tested to ensure that it meets the criteria for validity and reliability (Fornell & Larcker, 1981). CFA was conducted to assess the measurement model and to identify any validity and reliability concerns. First, items whose factor loadings were less than 0.5 were removed as suggested by Hair et al. (2010). Then, items that caused any serious issues in terms of reliability of the constructs, discriminant validity or convergent validity, were removed from the dataset. As a result of the validity examination, the entire construct for cognitive-behavioral control had to be removed. Finally, a total of 31 items were retained for the final measurement model. Table 3 shows the factor loadings of the retained items.

Next, the utilized analysis methods to assess the measurement model as well as the results of those analysis are discussed and presented in further detail.

TABLE 3 Standardized factor loadings

Item	HAB	EU	PI	PS	CEP	CP	EM	ST	TE	LI	CBC
HAB1	0,631										
HAB2	0,891										
HAB3	0,76										
HAB6	0,685										
EU1		0,648									
EU2		0,937									
EU3		0,845									
PI1			0,56								
PI2			0,574								
PI3			0,901								
PI4			0,951								
PS1				0,851							
PS2				0,906							
PS3				0,742							
PS4				0,859							
CP					0,897						
EM					0,894						
CP1						0,821					
CP2						0,841					
CP3						0,809					
EM1							0,742				
EM2							0,685				
EM4							0,772				
TE								0,938			
LI								0,915			
TE1									0,787		
TE2									0,856		
TE3									0,806		
TE4									0,834		
LI1										0,631	
LI2										0,811	
LI3										0,859	
CBC1											0,842
CBC2											0,661
CBC3											0,744

Note: HAB = Smartphone habits; EU = Excessive use of smartphones; PI = Privacy concerns; PS = Perceived stress; CEP = Cognitive-emotional preoccupation with using smartphones; CP = Cognitive preoccupation with using smartphones; EM = Emotional preoccupation with using smartphones; ST = Strain; TE = Techno-exhaustion; LI = Life invasion; CBR = Cognitive-behavioral control over using smartphones.

7.2.1 Reliability, Convergent validity and Discriminant validity

The measurement model was evaluated by examining construct reliability, convergent validity, and discriminant validity values. Reliability was examined by calculating Cronbach's Alpha and composite reliability (CR) for each construct. These are commonly used measures to check construct reliability (Hair et al., 2010). Cronbach's Alpha and CR measure internal consistency between the indicator items in a construct. The widely accepted threshold value for Cronbach's Alpha and CR to meet the adequate reliability is 0,7 (Chin, 1998; Hair, Anderson, Tatham & Black, 1988; Nunnally, 1978). Tables 4 and 5 show that the Cronbach's Alpha values range from 0,776 to 0,960 and CR values range from 0,833 to 0,925, thus demonstrating internal consistency are reliability of the constructs.

Convergent validity was tested by checking that the factor loadings of indicator items for the constructs are all statistically significant and exceed the threshold value of 0,5 (Hair et al., 2010). Also, to show reasonable level of convergent validity the Average Variance Extracted (AVE) values for all constructs should be higher than 0,5 as suggested by Chin (1998). The results from CFA show that the factor loadings range from 0.560 to 0.951 and AVEs range from 0,559 to 0,860. Hence, all figures meet the conditions for adequate convergent validity.

Discriminant validity should be tested to ensure that the items that theoretically should not be highly correlated to each other are not in fact correlated to each other (Campell & Fiske, 1959). In other words, the items should differ from one another (Campell & Fiske, 1959). To demonstrate discriminant validity, indicators of a construct should not highly correlate with indicators of other constructs (Campell & Fiske, 1959). This was tested by comparing the square root of AVE for a construct to the inter-construct correlation coefficients. The square root of the AVE for a construct should be greater than the inter-construct correlations to exhibit discriminant validity among constructs (Chin 1998; Fornell & Larcker, 1981). In this examination of discriminant validity, the construct for Cognitive-Behavioral control (CBC) had to be removed due to validity issues. Many of the indicator items for the CBC construct were highly correlated with the indicator items of other constructs. The square root of AVE for the CBC construct was also lower than some of the inter-construct correlations. As for the retained constructs, the correlation matrix in table 5 shows that the square roots of AVEs were all greater than the inter-construct correlation coefficients, indicating satisfactory discriminant validity among the constructs. To conclude, the results of the CFA showed acceptable reliability and validity of the measurements for the main research model.

TABLE 4 Results of descriptive statistics and reliability and confirmatory factor analysis. All factor loadings are significant at the p < 0.001 level. SD = Standard deviation.

Construct	**Kurtosis (skew)**	**Mean**	**SD**	**Loadings**	**Cronbach's alpha**
Habit (HAB)	11,8 (-2,85)	4,70	0,672	0,631–0,891	0,836
Excessive Use (EU)	-0,756 (-0,140)	4,67	1,63	0,648–0,937	0,853
Privacy Invasion (PI)	0,178 (-0,789)	5,25	1,40	0,560–0,951	0,813
Perceived Stress (PS)	0,307 (1,02)	1,99	0,983	0,742–0,906	0,904
Cognitive-emotional Preoccupation (CEP)	-0,531 (0,234)	3,37	1,05	0,894–0,897	0,942
Cognitive preoccupation (CP)	-0,502 (0,470)	2,84	1,12	0,809–0,841	0,852
Emotional preoccupation (EM)	-0,660 (0,117)	3,45	1,16	0,685–0,772	0,776
Strain (ST)	-0,921 (0,061)	2,69	1,13	0,915–0,938	0,960
Life Invasion (LI)	-1,10 (0,001)	2,59	1,11	0,631–0,859	0,812
Techno-exhaustion (TE)	-0,866 (0,197)	2,74	1,21	0,787–0,856	0,902
Cognitive-Behavioral Control (CBC)	-0,661(0,341)	3,01	1,43	0,661-0,842	0,786

TABLE 5 Correlation matrix, reliability, maximum shared variance, AVE, square root of AVE

	CR	**AVE**	**MSV**	**MaxR(H)**	**HAB**	**EU**	**PI**	**PS**	**CEP**	**ST**
HAB	0,833	0,559	0,157	0,871	**0,748**					
EU	0,856	0,670	0,387	0,917	0,396	**0,819**				
PI	0,845	0,590	0,031	0,936	-0,175	-0,046	**0,768**			
PS	0,906	0,708	0,195	0,918	0,020	0,099	-0,017	**0,842**		
CEP	0,890	0,802	0,753	0,890	0,171	0,622	0,122	0,442	**0,896**	
ST	0,925	0,860	0,753	0,925	0,010	0,502	0,163	0,247	0,868	**0,928**

Note: CR = Composite reliability, AVE = Average variance extracted, MSV = Maximum shared variance, MaxR(H) = Maximum reliability. The square root of the AVE of each construct is in bold on diagonal line.

Tables 4 and 5 supports composite reliability, convergent validity and discriminant validity of the constructs as CR scores for the constructs are all higher than 0,7, maximum shared variance (MSV) is less than AVE in all constructs, maximum reliability (MaxR(H)) is greater than CR in all constructs and the square root of AVEs for the constructs are all greater than the inter-construct correlations.

7.2.2 Measurement model fit statistics

The measurement model was tested by using the data collected from the survey. CFA and the fit indices for the model were calculated using IBM SPSS AMOS version 26. Commonly accepted criteria were applied to affirm a valid model fit, for example, Chi-square/df < 5, CFI > 0,9, IFI > 0,9, TLI > 0,9 and RMSEA < 0,08 (Anderson & Gerbing, 1988; Hair et al., 2010; Awang, 2012).

The results of the CFA show that the proposed measurement model exhibits adequate fit to the data [χ^2(437,2); df = 329; χ^2/df = 1,329; CFI = 0,945; IFI = 0,946; TLI = 0,936; and RMSEA = 0,054, with 90% confidence interval of (0,039-0,067)]. These values indicate that the model was a good fit according to the suggested estimates.

7.2.3 Common method bias

Since all the data were collected at same time and by using the same instrument, this study could be a subject to common methods bias (Podsakoff, MacKenzie, Lee & Podsakoff, 2003). Therefore, it is important to test for common method bias to make sure that the methods are not influencing the variance in the observed data or the correlations. First, IBM SPSS v.26 factor analysis methods were used to conduct Harman's single factor test to identify common method variance in the observed data (Podsakoff et al., 2003). Unrotated factor analysis using principal axis factoring was applied to all indicator items in the measurement model (Malhotra, Kim & Patil, 2006). Common method bias is argued to be present when a single factor is explaining more than 50 percent of the total variance (Podsakoff et al., 2003). The results of the Harman's single factor test revealed that only 30,2 percent of the total variance is explained by the single factor indicating a low likelihood of the common method bias threat.

Second, the correlation matrix was examined for extremely high correlations (r > 0,90), since they can be indicators of common method bias (Pavlou, Liang & Xue, 2007). No high correlations between variables were identified in the correlation matrix indicating that method bias is not a concern in this study.

Third, a common latent factor technique was applied to identify common method bias. In this approach a new latent factor was included to the measurement model and all measured items were related to that factor in addition to their latent factors (i.e., the constructs). The variance of the common factor was constrained to be 1 and the paths from the latent common factor to the items were constrained to be equal. The common variance was then estimated as the square of the unstandardized regression weights of the common factor. As a result, the common variance was 22% which is well under the commonly considered threshold of 50% to provide evidence for common method bias (Eichhorn, 2014). Thus, common method bias should not pose a significant issue is this study.

7.2.4 Multicollinearity

Multicollinearity problems occur when two or more independent variables are highly related to each other (Hair et al., 2010; Tabachnick & Fidell, 2013). Multicollinearity among variables can cause unnecessary error terms to be included in the model and increase the standard error of regression coefficients, thus decreasing the reliability of the results (Hair et al., 2010). In this study, multicollinearity was tested by checking the correlation matrix for highly related variables and by examining tolerance and Variance Inflation Factor (VIF) scores using regression results provided by the IBM SPSS v.26 collinearity diagnostic results. The examination of tolerance and VIF scores is argued to be the most reliable statistical test for multicollinearity (Hair et al., 2010; Pallant, 2010).

By viewing the correlation matrix, clear evidence for multicollinearity is provided if any correlation between independent variables is 0,9 or higher (Hair et al., 2010). Furthermore, it is suggested that correlation value as high as 0,7 between independent variables is enough to show multicollinearity (Pallant, 2010). Table 5 shows that none of the independent variables was highly correlated with any other independent variable and that all the correlations between independent variables are below the threshold of 0,7. Thus, high correlation among the variables is not a significant problem in this study.

Table 6 shows the collinearity diagnostic results from the regression analysis. According to Hair et al. (2010) and Pallant (2010) multicollinearity does not exist when tolerance values are above 0,10 and VIF values are below 10. The table 6 provides evidence that the tolerance values range between 0,368 and 0,783 and VIF values range from 1,276 to 2,751. Thus, multicollinearity should not be an issue in this study.

TABLE 6 Results of multicollinearity analysis based on tolerance and Variance Inflation Factor (VIF) values when habit, excessive use, cognitive-emotional preoccupation and perceived stress are predicting the dependent variable strain

Construct	**Tolerance**	**VIF**
Habit	0,783	1,276
Excessive Use	0,395	2,533
Cognitive-emotional Preoccupation	0,368	2,751
Perceived Stress	0,692	1,445

7.3 Structural causal model and hypotheses testing

The structural model was build using the validated latent factors with their observed items. SEM was then employed to evaluate the theorized structural causal model. First, overall fit indices for the model were calculated using IBM SPSS AMOS v.26 with Maximum Likelihood estimates. The fit values of the model were all within commonly accepted range [χ^2(594,48); df = 433; χ^2/df=1,373; CFI = 0,920; IFI = 0,923; TLI = 0,909; and RMSEA = 0,057 (with 90 percent confidence interval of 0,046-0,068)] (Anderson & Gerbing, 1988; Hair et al., 2010; Awang, 2012). Thus, the results demonstrate a valid model fit (see figure 5). Table 7 summarizes the standardized significant direct and indirect effects in the structural model. The indirect effects were examined by using a bootstrapping estimation with 2000 resamples to determine the significance of the mediated relationships.

The results from testing the main research model can be seen in figure 5. The model shows estimated path coefficients with significance levels. The results indicate that smartphone habits explained 8,5% of the variance in smartphone screentime and 4,3% of the variance in smartphone use frequency. Further, the model explains 38,6% of the variance in excessive use, 41,2% of the variance in cognitive-emotional preoccupation, 78,6% of the variance in strain, and 10,6% of the variance in privacy invasion.

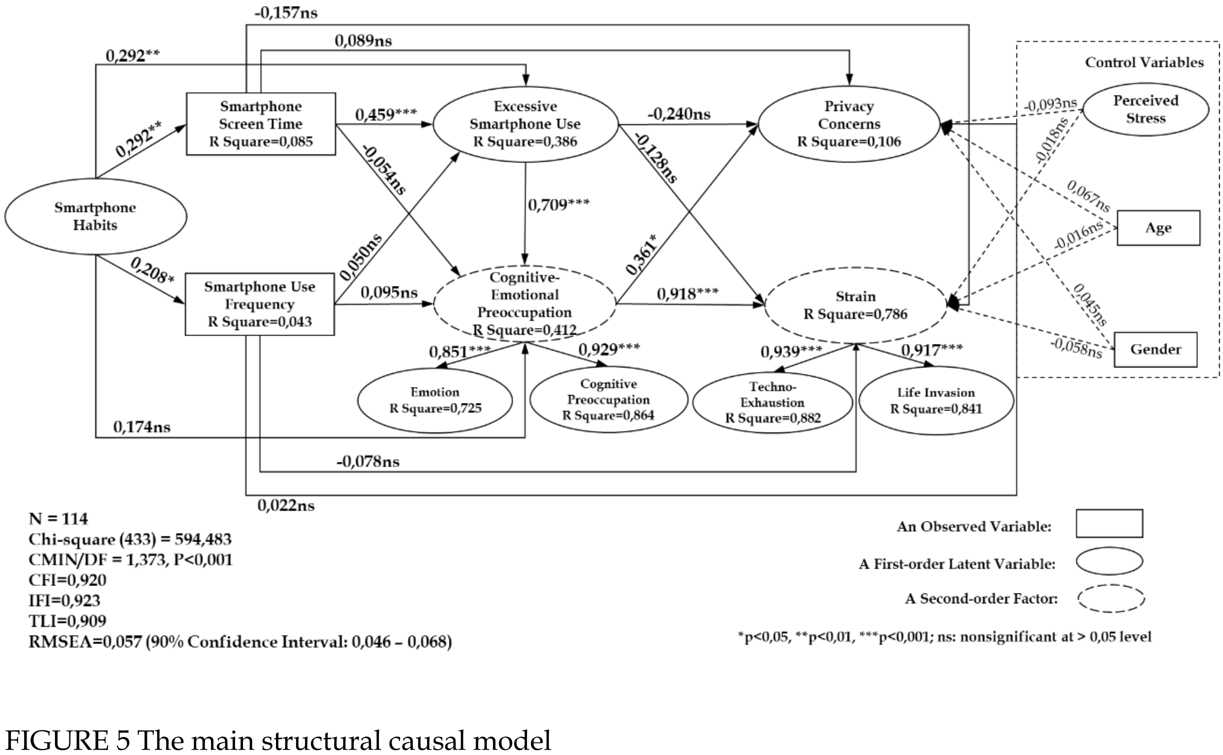

FIGURE 5 The main structural causal model

The results of the hypotheses testing provided support for 10 out of 17 hypotheses at least at the $p < 0,05$ significance level. Notwithstanding the rejection of seven hypotheses, the proposed model pictures an appropriate explanation for habitual and problematic smartphone behaviors as well as for the formation of negative consequences due to smartphone use.

The results indicate that strong habits over using smartphones are significant determinants of increased smartphone usage in terms of screen time accumulation and smartphone use frequency. A significant positive relationship between smartphone habits and smartphone screen time was observed (H1a: $\beta = 0,292$, $p < 0,001$). The hypothesis H1a was supported. Smartphone habits also had a significant positive effect on smartphone use frequency (H1b: $\beta = 0,208$, $p < 0,05$), thus supporting the H1b hypothesis. Smartphone habits had also a significant positive effect on excessive use of smartphones (H1c: $\beta = 0,292$, $p<0,01$). Furthermore, smartphone habits had a significant positive indirect effect on excessive use of smartphones that was mediated through increased screen time ($\beta = 0,145$, $p<0,001$). H1c was therefore fully accepted. Finally, smartphone habits had a significant positive indirect effect on cognitive-emotional preoccupation with using smartphones that was mediated through screen time and excessive use of smartphones ($\beta = 0,310$, $p<0,001$). H1d was partially supported as the direct effect was nonsignificant.

Next, the results indicate the increased use of smartphones influences excessive use of smartphones, cognitive-emotional preoccupation with using smartphones and negative consequences. As predicted in H2a, increased levels of screen time positively influenced excessive use of smartphones (H2a: $\beta = 0,459$, $p < 0,001$). H2a was supported. Increased screentime had also significant positive indirect effect on cognitive-emotional preoccupation with using smartphone ($\beta = 0,345$, $p < 0,001$) supporting hypothesis H2b. The indirect effect from screen time to cognitive-emotional preoccupation was mediated through excessive use of smartphones. Furthermore, increased levels of screen time indirectly influenced strain through excessive use and cognitive-emotional preoccupation with using smartphones (0,256, $p < 0,05$). H2c was partially supported. Screen time had nonsignificant effects on privacy concerns, thus hypothesis H2d was rejected.

Interestingly, smartphone use frequency did not have any significant direct nor indirect effects on excessive use, cognitive-emotional preoccupation with using smartphone or negative consequences. Thus, the hypotheses H3a-H3d were rejected.

Consistent with H4, the results showed that excessive use of smartphones had a highly significant positive association to cognitive-emotional preoccupation with using smartphones (H4: $\beta = 0,709$, $p < 0,001$). Hypothesis H4 was accepted. Excessive smartphone use was also expected to positively influence the formation of negative consequences such as strain and privacy concerns. While the results did not provide support for direct effects from excessive use to negative consequences, indirect effects were observed. The significant positive relationship between excessive use and strain was fully mediated through cognitive-emotional preoccupation ($\beta = 0,651$, $p < 0,001$). H5a was accepted. Similarly, the relationship between excessive use and privacy concerns was fully mediated through cognitive-emotional preoccupation with using smartphones (β = 0,256, p < 0,001). H5b was therefore also accepted.

Cognitive-emotional preoccupation was expected to be important determinant of negative consequences such as stain caused by smartphone use and privacy concerns. The structural model supported this prediction by demonstrating that cognitive-emotional preoccupation positively influences strain caused by smartphone use and privacy concerns with path coefficients at 0,918 (p < 0,001) and 0,361 (p < 0,05), respectively. Hypotheses H6a and H6b were fully supported.

The effects of age, gender and perceived stress on the dependent variables were controlled in the model. The control variables had no effect on strain due to smartphone use or privacy concerns at p < 0,05 significance level.

To conclude, the findings provide support for the key research model and demonstrated how smartphone habits lead to increased use of smartphones which further contributes to the development of problematic cognitive, emotional and behavioral patterns with smartphone use which eventually lead to negative consequences, such as strain and privacy concerns (see figure 6).

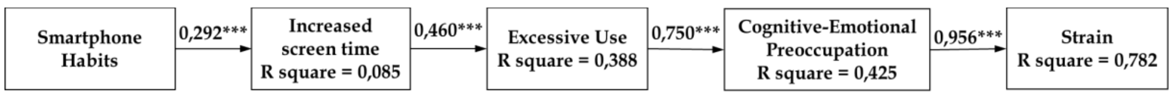

FIGURE 6 The results of the main model support the theorized sequential development process of problematic smartphone use and negative consequences

TABLE 7 Results of the main model

Hypotheses	Direct effects β	Indirect effects β	Total effects β	Result
H1a: Habitual smartphone use leads to increased smartphone use in terms increased screen time	0,292***	-	0,292***	Supported
H1b: Habitual smartphone use leads to increased smartphone use in terms of increased use frequency	0,208**	-	0,208**	Supported
H1c: Habitual smartphone use positively influences excessive use of smartphones	0,292**	0,145***	0,438***	Supported
H1d: Habitual smartphone use positively influences cognitive-emotional preoccupation with using smartphones	-	0,310***	0,310***	Partly supported Full mediation
H2a: Smartphone screen time is positively related to excessive use of smartphones	0,459***	-	0,457***	Supported
H2b: Smartphone screen time is positively related to cognitive-emotional preoccupation with using smartphones	-	0,345***	0,345***	Partly supported Full mediation
H2c: Smartphone screen time is positively related to strain due to smartphone use	-	0,256*	0,256*	Partly supported Full mediation
H2d: Smartphone screen time is positively related to privacy concerns	-	-	-	Rejected
H3a: Smartphone use frequency is positively related to excessive use of smartphones	-	-	-	Rejected
H3b: Smartphone use frequency is positively related to cognitive-emotional preoccupation with using smartphones	-	-	-	Rejected
H3c: Smartphone use frequency is positively related to strain due to smartphone use	-	-	-	Rejected
H3d: Smartphone use frequency is positively related to privacy concerns	-	-	-	Rejected
H4: Excessive use of smartphones is positively related to cognitive-emotional preoccupation with using smartphones	0,709***	-	0,709***	Supported
H5a: Excessive use of smartphones is positively related to strain due to smartphone use	-	0,651***	0,651***	Partly supported Full mediation
H5b: Excessive use of smartphones is positively related to privacy concerns	-	0,256*	0,256*	Partly supported Full mediation
H6a: Cognitive-emotional preoccupation with using smartphones is positively related to strain due to smartphone use	0,918***	-	0,918***	Supported
H6b: Cognitive-emotional preoccupation with using smartphones is positively related to privacy concerns	0,361*	-	0,361*	Supported

7.3.1 Further examination of the relationships between increased use of smartphone and negative consequences

The mediating effects of smartphone screen time and use frequency on cognitive-emotional preoccupation, strain, and privacy invasion were further examined to determine under what circumstances the significant relationship is mediated. Bootstrapping estimation with 2000 resamples was used to estimate the indirect effect of the proposed mediator factors. Table 8 summarizes the significant effects found in this closer examination.

First, as shown in figure 7, the results demonstrated that the significant positive relationship between smartphone screen time and strain was fully mediated through excessive use and further through cognitive-emotional preoccupation with using smartphones (indirect effect β = 0,304, p < 0,001). No other significant indirect effects were observed in this model at p<0,05 significance level.

Also, another interesting finding in the relationship between screen time and strain was made as screen time had significant negative direct effect on strain. (β = -0,163, p < 0,05). This finding is further discussed later in this section and in the discussion section.

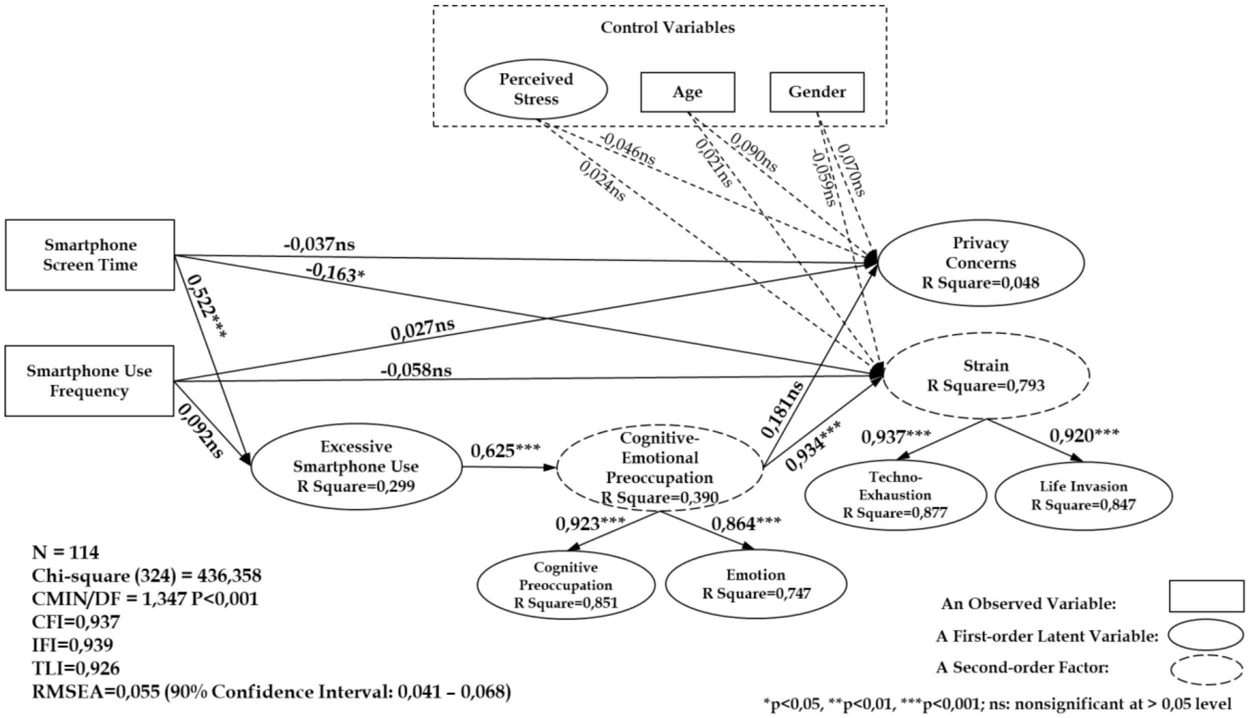

FIGURE 7 Excessive use and cognitive-emotional preoccupation mediate the relationship between screen time and strain

Next, the model shown in figure 8 was tested. The results from this model demonstrated that the significant positive relationship between screen time and strain caused by smartphone use was fully mediated through cognitive-emotional preoccupation with using smartphones (indirect effect β = 0,255, p < 0,01).

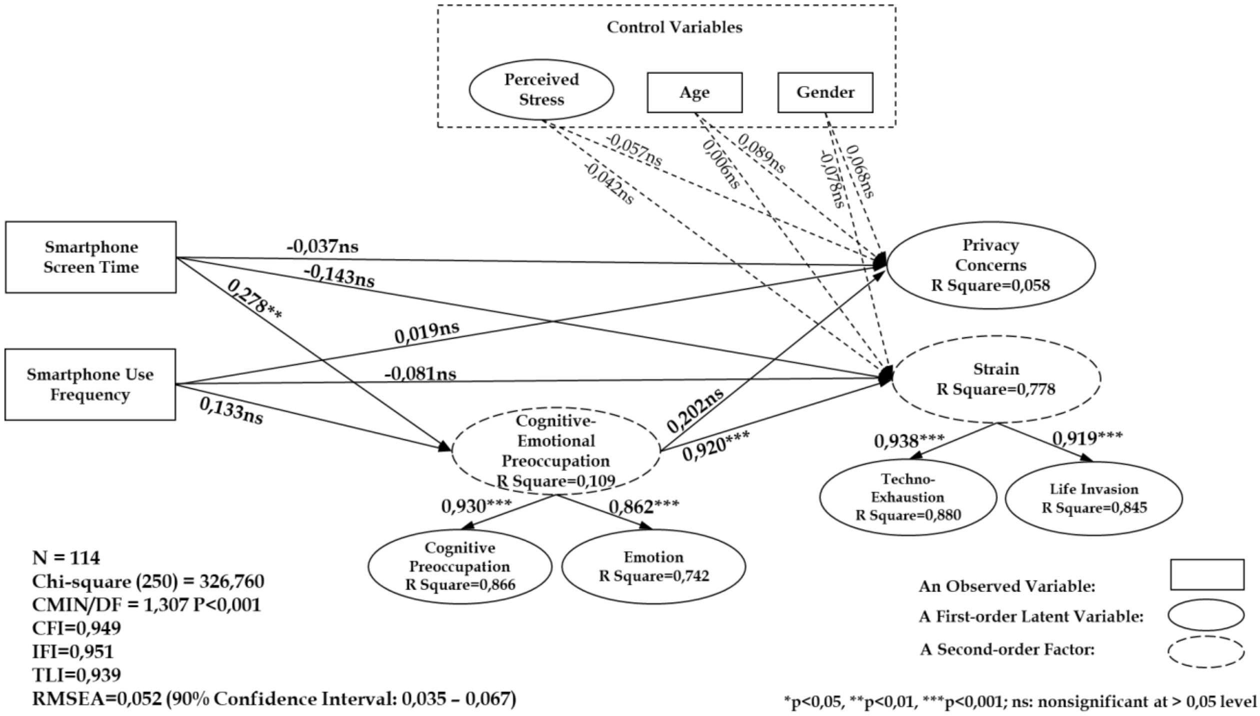

FIGURE 8 Cognitive-emotional preoccupation mediates the relationship between screen time and strain

Finally, the direct and indirect effects in the model shown in figure 9 were tested. The results from testing this model showed that screen time had a direct significant negative effect on strain (β = -0,292, p < 0,05). However, the observed indirect effect that was mediated through excessive use of smartphones was significant and positive (indirect effect β = 0,313, p < 0,01). While the negative direct effect from screentime to strain is contradicting the proposed hypothesis H2c, it is consistent with the theoretical framework which suggested that excessive use of smartphones is a necessary condition to experience negative outcomes (Cao et al., 2018; Davis, 2001; Zheng & Lee, 2016). Therefore, as demonstrated in all the models shown in figures 5, 7, 8 and 9, increased use of smartphones does not automatically lead to negative outcomes.

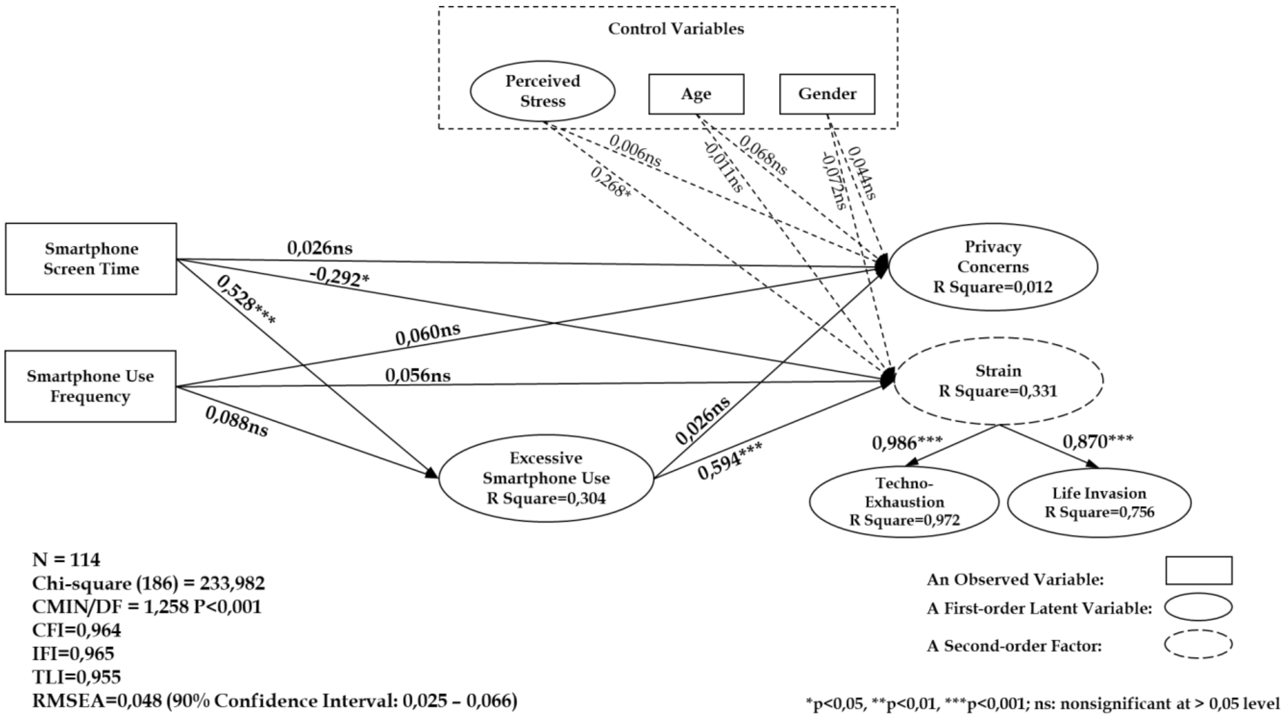

FIGURE 9 Excessive use mediates the relationship between screen time and strain

TABLE 8 Mediated relationships between screen time and strain/privacy concerns; and between use frequency and strain/privacy concerns

Mediating relationship	**Direct effects β**	**Indirect effects β**	**Total effects β**	**Result**
Screen time → Excessive use → Cognitive-emotional preoccupation → Strain	-0,163*	0,304***	0,141*	Partial mediation
Screen time → Excessive use → Cognitive-emotional preoccupation → Privacy concerns	-	-	-	No effect
Use frequency → Excessive use → Cognitive-emotional preoccupation → Strain	-	-	-	No effect
Use frequency → Excessive use → Cognitive-emotional preoccupation → Privacy concerns	-	-	-	No effect
Screen time → Cognitive-emotional preoccupation → Strain	-	0,255**	0,255**	Full mediation
Screen time → Cognitive-emotional preoccupation → Privacy concerns	-	-	-	No effect
Use frequency → Cognitive-emotional preoccupation → Strain	-	-	-	No effect
Use frequency → Cognitive-emotional preoccupation → Privacy concerns	-	-	-	No effect
Screen time → Excessive use → Strain	-0,292*	0,313**	0,021*	Partial mediation
Screen time → Excessive use → Privacy concerns	-	-	-	No effect
Use frequency → Excessive use → Strain	-	-	-	No effect
Use frequency → Excessive use → Privacy concerns	-	-	-	No effect

7.3.2 The moderating effect of cognitive-behavioral control

The items for cognitive-behavioral control were highly correlated with some of the items for the other factors, indicating a discriminant validity issue. As shown in table 9, the square root of the AVE for strain and cognitive-behavioral control were less than the absolute values of the correlations with other factors. The AVEs for cognitive-behavioral control and strain were also less than their maximum shared variance (MSV) (see table 9 below). As a result, the construct for cognitive-behavioral control was discarded from the main measurement and structural model. However, while acknowledging that the measures do not support discriminant validity and the results must be thus carefully interpreted, the interaction effect of cognitive-behavioral control was tested accordingly following process suggested by Baron and Kenny (1986). The results from testing the moderating effect show that cognitive-behavioral control dampened the positive relationship between cognitive-emotional preoccupation and strain (interaction term: β = -0,156, p < 0,05). Interestingly, cognitive-behavioral control had also a significant positive association with strain (β = 0,777, p < 0,001). This finding is discussed further in the discussion section. Figure 10 shows the model that was used to test the moderation effect. The interaction term in the model is the product of cognitive-emotional preoccupation and cognitive-behavioral control. The results of the moderation model testing support hypothesis H7b (see table 10). The moderating effect of cognitive-behavioral control is further plotted in figure 11.

TABLE 9 Correlation matrix, reliability, maximum shared variance, AVE and square root of AVE when cognitive-behavioral control is not removed

	CR	**AVE**	**MSV**	**MaxR(H)**	**CEP**	**PI**	**PS**	**ST**	**CBC**
CEP	0,889	0,801	0,728	0,894	**0,895**				
PI	0,845	0,590	0,024	0,935	0,129	**0,768**			
PS	0,906	0,708	0,187	0,918	0,432	-0,016	**0,841**		
TS	0,925	0,861	0,887	0,945	0,853	0,156	0,257	**0,928**	
CBC	0,795	0,566	0,887	0,817	0,801	0,141	0,160	0,942	**0,753**

Note: CR = Composite reliability, AVE = Average variance extracted, MSV = Maximum shared variance, MaxR(H) = Maximum reliability. The square root of the AVE of each construct is in bold on diagonal line.

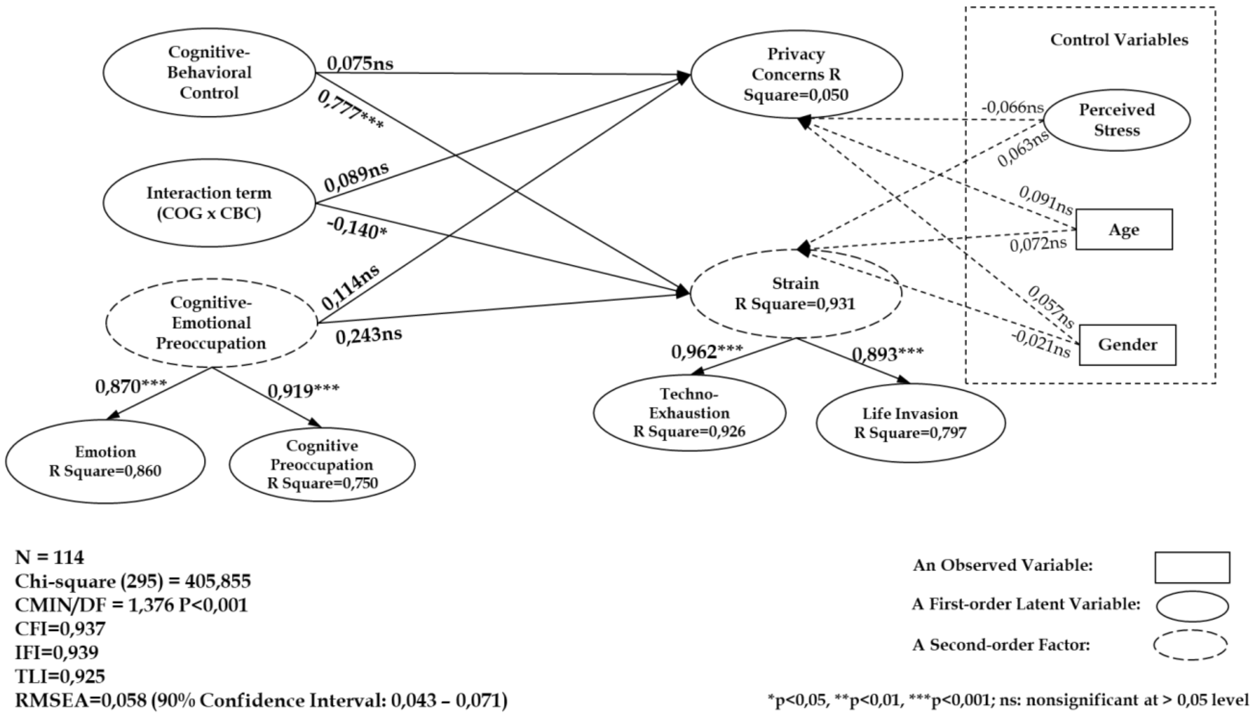

FIGURE 10 The moderation model

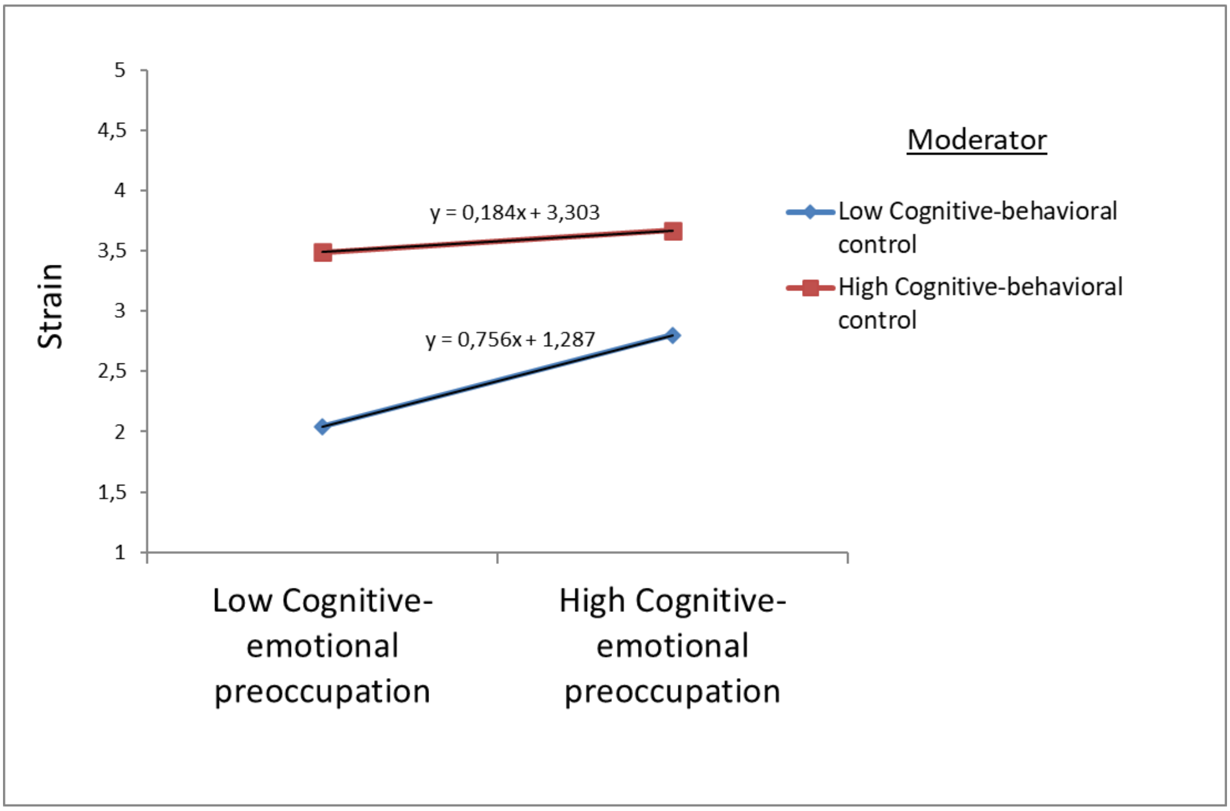

FIGURE 11 Plot of the moderating effect

TABLE 10 The results of the moderation model

Hypotheses	**Interaction term effect β**	**Result**
H7a: Cognitive-behavioral control over smartphone use dampens the positive relationship between cognitive-emotional preoccupation with using smartphones and privacy concerns	-	Rejected
H7b: Cognitive-behavioral control over smartphone use dampens the positive relationship between cognitive-emotional preoccupation with using smartphones and strain due to smartphone use.	-0,140*	Supported (though the result may be biased due to validity issues)

8 DISCUSSION

In 2019, data collected from 11000 smartphone users' devices showed that most people spent 3 hours 15 minutes every day on smartphones (MacKay, 2019). In the United States the number was 3 hours 43 minutes (He, 2019) and in United Kingdom it was 3 hours 23 minutes (CodeComputerLove, 2019). In this study the number was a little higher as respondents spent 3 hours and 58 minutes on their smartphones a day on average. However, the vast majority of the respondents stated that they spend too much time on their smartphones. These statistics raise a series of questions to which this study attempts to answer. First, why do people use smartphones more than they would really want to? Second, what kinds of negative consequences can such excessive use of smartphones cause to users? And third, how does smartphone use lead to problematic smartphone use and negative consequences? As problematic smartphone use seems to be largely unplanned, unintentional and irrational behavior, a theoretical framework explaining impulsive, unplanned, and unintentional behavior was used to answer these questions.

To answer the first question, this study provided support for that smartphone use can be explained by habitual behavior that is not always in line with one's intention, plans and long-term goals. Habits are generally defined as "learned sequences of acts that have become automatic responses to specific cues" (Verplanken & Aarts, 1999, p. 104). Almost all of the respondents agreed that using smartphones had become automatic and natural to them. This suggests that the respondents had developed strong habits of using smartphones. Repetitive behavior can also indicate the presence of strong habits (Wood et al., 2002). The results showed that respondents used their smartphones 76 times a day on average, which supports the claim that people use smartphones habitually. Such repetitive smartphone use behavior suggests that most of the respondents had developed a so-called checking habit, which has been referred in prior studies as problematic and compulsive behavior (Lee et al., 2014; Oulasvirta et al., 2012; Van Deursen et al., 2015). The results showed also that habitual smartphone use was a strong determinant for increased levels of smartphone use as well as excessive smartphone use. Increased levels of smartphone use were expected because habits are performed with high levels of automaticity and low the levels of effort (Ouellette & Wood, 1998; Wood et al., 2002). Thus, the results suggest that people use smartphones unintentionally for hours every day. Also, extant behavioral studies suggest that once habits are formed, people often continue to repeat them when they are no longer appropriate, effective responses and even when they are conflicting with intentions (Wood et al., 2002; Wood & Rünger, 2016). The results are consistent with habit formation theories and suggest that people continue to overuse smartphones out of habit even though their intentions would be to reduce their smartphone use. Hence, this study provides an important insight into smartphone use in the modern world and demonstrates how habits can drive high levels of smartphone usage in terms of screen time accumulation and smartphone use frequency.

In addition to habitual smartphone use, the findings indicate that majority of smartphone users in this study used smartphones excessively. As suggested, excessive use was measured as the extent to which the respondents themselves thought that they were using smartphones too much, i.e., excessively (Caplan & High, 2006). Excessive use of smartphones was found to be a strong predictor of cognitive-emotional preoccupation with using smartphones. This finding is in line with prior research on problematic smartphone use and supports the proposition that excessive use is a major reason that causes persistent, obsessive and disturbing thoughts about smartphone use (Cao et al., 2018; Lee et al, 2014; Zheng & Lee, 2016). In prior literature, excessive use has been conceptualized as a necessary cause for users to develop maladaptive cognitions and further negative consequences (Davis, 2001; Zheng & Lee, 2016). In problematic behaviors a necessary cause must be present or must have occurred in order for the adverse effects to occur (Davis, 2001). The findings of this study support this conceptualization of excessive use as a necessary cause of cognitive-emotional preoccupation and negative consequences from smartphone use. Smartphone habits and increased use of smartphone did not have any direct effects on cognitive-emotional preoccupation with using smartphones or further on negative consequences due to smartphone use. However, both habitual and increased use of smartphones indirectly contributed to the formation of cognitive-emotional preoccupation through excessive use of smartphones. Excessive use also mediated the relationship between increased use of smartphones and strain. Thus, this study confirms that high levels of smartphone use only lead to problematic smartphone use and negative consequences when excessive use is present.

Consistent with prior studies, cognitive-emotional preoccupation with using smartphones was found to be positively associated with negative consequences such as strain and privacy concerns (Cao et al., 2018, Lee et al., 2014; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). In prior studies cognitive-emotional preoccupation has been conceptualized as a sufficient proximal cause of problematic smartphone use and negative outcomes (Cao et al., 2018; Davis, 2001; Turel & Qahri- Saremi, 2016; Zheng & Lee, 2016). Unlike necessary cause, the presence or occurrence of sufficient cause guarantees the occurrence of the adverse effects (Davis, 2001; Zheng & Lee, 2016). Thus, cognitive-emotional preoccupation is a key factor that places individuals at risk for problematic behaviors (Collins & Lapp, 1992). It generates impulsions towards a behavior which reinforce people's urges to engage in the behavior (Turel & Qahri-Saremi, 2016). The results were consistent with this conceptualization indicating that smartphone users in the current study had developed strong thoughts and emotional attachments with using smartphones. For instance, majority of the participants used smartphones in response to negative emotions such as loneliness, boredom and anxiety. Preoccupation can also be annoying and disturbing as concentrating on other tasks can become difficult when thoughts about smartphone constantly distract attention (Oulasvirtra et al, 2011; Turel & Qahri-Saremi, 2016). High levels of cognitive-emotional preoccupation may also indicate the presence of smartphone addiction syndrome which can further lead to other detrimental consequences (Cao et al., 2018; Davis, 2001; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016).

To answer the second research question, the findings provide support for the proposition that excessive smartphone use contributes to the formation of strain and privacy concerns as negative consequences from smartphone use. Strain in this study referred to the experiences of stress and exhaustion due to the invasive characteristics of smartphones. Privacy concerns referred to a negative perception in which individuals feel that their privacy has been compromised due to inability possibility to control personal information on smartphone applications.

To answer the third and final research question, the results demonstrated a sequential development process of problematic smartphone use that ultimately led to negative consequences. The main research model encapsulated the theoretical framework that was used to explain how habitual smartphone use was positively associated with increased and excessive use of smartphones which in turn induced cognitive-emotional preoccupation as a stress creating condition which eventually caused smartphone users to experience strain and privacy concerns as negative consequences. Excessive use and cognitive-emotional preoccupation with using smartphones were found to be essential factors to experience negative consequences from smartphone use.

Excessive use and cognitive-emotional preoccupation are important factors in explaining negative consequences because the results showed that increased smartphone use alone is not sufficient condition to induce negative consequences from smartphone use. This finding could be explained in various ways. For instance, people may have jobs where they must use smartphones throughout the day which can lead to high levels of smartphone use but not to problematic cognitive, emotional or behavioral patterns or negative consequences. Also, it is important to note that smartphone use can have various positive effects too. For instance, hedonic use of social media has been found to have a positive side which can increase productivity and work performance (Ali-Hassan, Nevo & Wade, 2015). Thus, increased smartphone use can actually lead to positive outcomes instead of negative ones. This could explain why screen time was negatively associated to strain in two of the models in this study (figures 7 and 9). Also, prior research has suggested that users may overuse technologies without showing any signs of addiction or negative consequences (Charlton & Danforth, 2007). However, when excessive use and cognitive-emotional preoccupation were present, increased use of smartphones indirectly induced negative consequences through these mediating factors. Similarly, smartphone habits were only indirectly associated with cognitive-emotional preoccupation through excessive use.

Finally, the results showed that cognitive-behavioral control had a moderating effect on the positive relationship between cognitive-emotional preoccupation and strain. This finding suggests that individuals with strong cognitive-behavioral control over smartphone use can inhibit urges to engage in smartphone use and prevent users from experiencing negative consequences. This is consistent with prior studies examining problematic behaviors (Cao et al., 2018; Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016). Collins and Lapp (1992) originally examined this interaction effect in alcohol consumption. They found that individuals with difficulties controlling their alcohol consumption scored high on cognitive-emotional preoccupation and low on cognitive-behavioral control (Collins & Lapp, 1992). Turel and Qahri-Saremi (2016) as well as Cao et al. (2018) had similar results when examining problematic social media use on smartphones. However, it must be noted that in this study the measures used to test the moderation effect had validity issues and the results must be interpreted carefully.

Collins and Lapp (1992) also suggested that cognitive-behavioral control is relevant only when the individual is concerned about controlling the problematic behavior. Drawing from this logic, it can be argued that smartphone users must become aware of the negative consequences first in order to become motivated to restrict their smartphone use to avoid or alleviate the negative consequences. Turel and Qahri-Saremi (2016) extrapolated this logic into their model and found that cognitive-behavioral control was negatively associated with using smartphones in inappropriate places such as while on class, work, driving or talking face to face with people. This makes sense as people can imagine and understand the risks of using smartphones while driving, for instance, and thus become motivated to control their smartphone use while driving in order to mitigate the risks. Curiously, in this study cognitive-behavioral control had a significant positive effect on the negative consequence of strain in the moderation model ($\beta = 0{,}777$, $p < 0{,}001$, see figure 10). It can be argued that strain and privacy concerns are typically experiences that people become aware of and motivated to avoid once they have experienced them themselves first. Saying it differently, it can be difficult to become concerned excessive smartphone use if smartphone use is not considered as a strain creating factor in life. It is reasonable expect that people who experience exhaustion and feel that their personal life is being invaded by smartphones develop strong concerns about their smartphone use and are highly motivated to control it.

8.1 Contributions to research

This study contributes to the research on the dark side of IT use (Tarafdar et al., 2015). Drawing from several theoretical perspectives, this study built and empirically tested a theoretical model to understand the novel phenomenon of problematic smartphone use. Because of the lack of theory driven studies prior research has not yet succeeded to establish a common understanding of the conceptualization, drivers, and consequences of problematic smartphone use (Turel & Qahri-Saremi, 2016). Without a solid theoretical basis, inconsistent results can cause confusion and the results can be misinterpreted (Zheng & Lee, 2014). This study strengthens the theoretical foundation and expands the knowledge of problematic smartphone use. By focusing on exploring the underlying developmental process of problematic smartphone use and the negative consequences, this study identified several factors that contributed to the formation of problematic behaviors and negative consequences regarding smartphone use.

By utilizing theories that explain other more established problematic behaviors, such as problematic drinking and gambling, the proposed research model accomplished to explain sufficient variance in excessive smartphone use, cognitive-emotional preoccupation with using smartphones, and negative consequences attributed to smartphone use. Hence, the findings of this study suggest that problematic use of smartphones have similar features and contributing factors with other problematic behaviors. Therefore, this study also demonstrated that the factors used to explain other problematic behaviors can be used to indicate the presence of problematic smartphone behaviors too.

More specifically, this study contributes to bodies of literature on IT use, habit formation theories, dual-process theories, and technostress. The findings showed that day-to-day smartphone use seems to be voluntary, irrational and unplanned in nature. Hence, the perspectives from the habit formation theories and dual-process theories provide appropriate theoretical lenses for explaining smartphone use behaviors. This is an important contribution to the IS use literature that has traditionally relied on planned behavior-based models and rationality assumptions (Bhattacherjee, 2001; Turel & Qarhi-Saremi, 2016). Also, this study confirmed the propositions that technostress literature can be used to explain how smartphone use can affect the well-being of users (Boonjing & Chanvarasuth, 2017; Salo et al., 2019). Thus, the findings of this study provide important insights to technostress literature and enriches the understanding on the relationship between smartphone use and technostress.

Finally, in this study smartphone usage data, namely screen time and use frequencies, were collected straight from the users' devices. This enabled the current study to obtain a realistic picture of smartphone use in today. This is an important contribution to IT use research that has mainly relied on self-reported data to assess the extent of IT use in different instances. Especially, the data showed that smartphones play an important role in people's lives today.

8.2 Practical implications

The findings of this study showed that regular people tend to use smartphones excessively. Excessive smartphone use seems to be a growing universal problem and it has been found to expose users to various adverse effects such as difficulties to manage life, exhaustion, decreased academic performance, social problems and heightened psychological distress (Cao et al., 2018; Caplan & High, 2006; Chesley, 2005; Luqman et al., 2017; Turel & Qahri-Saremi, 2016; Zheng & Lee, 2016). The findings in this study complemented prior understanding by showing that excessive smartphone use is associated with strain and privacy concerns. Thus, excessive use of smartphones should be considered in practice (Zheng & Lee, 2016). Based on the findings, this study offers several practical implications for identifying, monitoring and controlling excessive and problematic use of smartphones.

Overall, this study raises awareness of excessive smartphone use and the possible impacts it may have on users' well-being. By understanding the underlying processes and mechanisms of problematic smartphone behavior people can better acknowledge their relationship to their smartphones. More specifically, by understanding that excessive smartphone usage can be attributed to automatic and impulsive responses that happen outside of one's awareness, attention and control, new ways can be implemented to make smartphone users become aware of their behavior regarding smartphone use as well as the behaviors of others around. For example, IT artifact developers and designers can make monitoring features and overuse reminders to smartphone applications to help users become aware of their smartphone usage and to govern it more properly.

Drawing from the results of the present study, at least two important aspects of smartphone use would be important to offer for people about their smartphone usage. First, the amount of smartphone usage. And second, the nature of the usage (i.e., what kind of usage the amount consists of). These aspects are important to acknowledge, because smartphone users are prone to underestimate their use of smartphones (Lin et al., 2015). Also, in order to learn to control impulsions it is important to understand the nature of the problematic behavior and the consequences it may have (Collins & Lapp, 1992; Turel & Qahri-Saremi, 2016).

However, it is important to note that there is no specific amount of smartphone usage that can be automatically considered as excessive or problematic. In many cases smartphone use can result in positive outcomes, such as increased productivity (Ali-Hassan et al., 2015). Findings of this study support the idea that the key factor determining the extent of negative consequences from smartphone use seems to be the user's perception of his/her smartphone use (Caplan & High, 2006). If smartphone use is considered as excessive by the user itself and the usage is mostly impulsive and irrational by nature, it can most often feel like the device is stealing the user's time. That can then lead to exhaustion and other consequences. Therefore, by acknowledging how much smartphones are used and how they are used, users can become aware of their habitual behavior which can encourage them to take action to reduce the problematic and harmful aspects of that behavior.

Understanding the behavioral and cognitive mechanisms that are involved in excessive smartphone use is also important. The cognitive and behavioral mechanisms and processes that take place when people are exposed to relevant stimulant cues have a significant effect on how people act and behave in everyday life (Carden & Wood, 2018). Yet the role of these mechanisms in guiding human behavior is often neglected. Several studies provide evidence that the more people are exposed to cues the more they will act out the automatic responses those cues provoke (Clements & Boyle, 2018; Wood et al., 2002). By understanding this, people can actively plan to reduce their exposure to the cues related undesired behaviors that they encounter throughout the day. In smartphone use several actions can be taken to reduce cues that trigger strong impulsions toward smartphone use. Examples of such measures could include switching off or muting the push notifications from smartphones, intentionally planning times when smartphone is not used and leaving smartphone to another room when trying to concentrate on something important, such as work or school assignments. In general, planning and making deliberate choices about smartphone can hinder the effects and strength of the spontaneous responses to cues and thus reduce undesired behaviors (Wood & Rünger, 2016).

However, as with other problematic behaviors, not all individuals are able to govern and self-regulate their problematic behaviors with smartphone usage. Also, some people might not want to voluntarily reduce their excessive use as they might not find it problematic. This is often the case especially with teenagers and individuals who lack self-control (Zheng & Lee, 2016). That is why other people and institutions such as parents, schools and organizations can help to identify and control problematic smartphone behaviors. For instance, educational institutions and parents can actively inform and educate students and children about the potential addictive and adverse effects of excessive smartphone use. As strains from IT use have been shown to negatively affect work performance, organizations could also educate their employees about the negative effects of excessive smartphone use (Ayyagari et al., 2011; Ragu-Nathan et al., 2008). Also, as problematic use of smartphones, such as using smartphones while listening to class lecture, has been shown to diminish students' academic performance (Cao et al. 2018; Turel & Qahri-Saremi, 2016), schools could implement practices where using smartphones on non-class purposes is prohibited or at least discouraged. Also, individuals could be encouraged to intervene if they detect problematic behaviors within their circle of acquaintances. For example, decline in academic performance, ignorance of the offline world, lack of sleep, eye strain, and the usage of smartphones at the expense of other important activities can be noticeable signs of a possible problematic smartphone behavior that parents and other people can detect. Parents can also enforce restrictions on how, when and how much smartphones are allowed to be used.

8.3 Limitations and future research

This study has several limitations that should be acknowledged when interpreting the findings. Moreover, these limitations can guide and inform future research. First, the sample size in the current study was relatively small for SEM which is commonly recognized as a large sample size technique. While there are no absolute guidelines regarding sample size requirements in SEM, some general rules of thumb for sufficient sample size are often suggested. Usually, a minimum sample size of 100-200 is recommended (Boomsma, 1982; Kline, 2005; Memon et al., 2020; Tabachnick & Fidell, 2001). Also, various sample-to-item or sample-to-variable ratios have been suggested (Memon et al., 2020). Small sample size may have increased both type I (false-positive) and type II (false-negative) errors, because non-significant results may have been deflated and significant results may have been inflated (Banerjee, Chitnis, Jadhav, Bhawalkar & Chaudhury, 2009). Thus, the results of this study should be interpreted with caution. Future studies should try to replicate the findings of this study with varying samples to obtain a better validity of the results.

Second, this study used a cross-sectional research design in which all the data were collected at one point in time via self-report questionnaire. The use of such research design makes this study vulnerable to the effects of common method variance. In other words, the variance in the model could be "attributable to the measurement method rather than to the constructs the measures are assumed to represent" (Podsakoff et al., 2003, p. 879). However, several statistical techniques indicated that common method variance does not appear to have a substantial effect in this study. Also, it is suggested that the effects of common-method variance might be generally exaggerated (Spector, 2006). As this study provides only a snapshot of excessive and problematic smartphone use, it cannot be used to determine whether these behaviors remain stable over time. Also, this study indicated the existence of a developmental process of smartphone related behaviors although this inference is limited with a cross-sectional design. Longitudinal studies would offer a better insight into the processes of how these behaviors develop over time. Longitudinal studies can also provide more accurate statistical inference on causality (Dillon & Goldstein, 1984). Therefore, future research should implement longitudinal research designs to gain more deeper understanding of smartphone and other IT use in general in voluntary settings.

Third, the sample in this study consisted chiefly of young adult population with similar cultural backgrounds within Finland. Culture significantly influences the way people use technologies and human behavior overall (Soper & Turel 2016). Thus, the generalizability of the findings to other cultural contexts is limited. Future research should consider this possible research gap and examine voluntary technology use further in different cultural settings and with varying demographics.

Fourth, excessive and problematic behaviors should be investigated further with other more qualitative approaches. For example, interviews could enable a deeper understanding of the factors that should be acknowledged when assessing excessive and problematic IT use behaviors. Also, people may fill self-report questionnaires in socially desirable ways, especially in relation to problematic behaviors.

Fifth, the data used in this study was gathered from voluntary participants. Prior research has suggested that volunteers can differ from those who do not volunteer within the same population (Heiman, 2002; Dodge et al., 2014).

Sixth, Finnish versions of the items were made and used in this study to collect data. The translated items might differ from the intent of the wording in the original language. Thus, the participants might have understood the questions slightly differently in the translated Finnish versions compared to the original items.

Finally, problematic IT use behaviors are still widely unexplored, and more effort is needed to gain better understanding of their underlying causes and consequences (Haagsma et al., 2013; Soror et al., 2015; Turel & Qahri-Saremi, 2016). Especially, as the use of smartphones is expected to grow in the future (Ericsson, 2017) and the adverse side effects will probably become more prevalent. The findings of this study confirmed that theoretical perspectives, such as habit formation theory and dual-process theories, that have been used to explain other problematic behaviors can be used to explain problematic behaviors regarding IT use. It is therefore reasonable assume that problematic IT use shares similar features with other more established problematic behaviors. Future research on problematic IT use could further borrow other established theoretical perspectives that have been used to explore problematic behaviors in other domains.

9 CONCLUSION

Smartphone use has increased rapidly over the last decades and this study confirmed that people use a substantial amount of their time on smartphones every day. Along with the numerous advancements that smartphones have enabled, increased smartphone use has been found to have unintended side effects. The purpose of this study was to obtain a better understanding of the adverse side effects that increased smartphone use can have.

Drawing from habit formation theories, dual-process theories and technostress literature, this study conflated a theoretical framework to understand the underlying causes of problematic behaviors and negative consequences regarding smartphone use. Furthermore, a theoretical model was built to examine the development of problematic behaviors and negative consequences regarding smartphone use. A survey among regular smartphone users was conducted to empirically test and validate the research model. Actual screen time and use frequency data were collected from tracking software that are pre-installed to most of the latest smartphone models.

The key hypotheses were supported by the results. Most importantly, the findings suggest that regular smartphone users are likely to develop problematic behavioral, cognitive and emotional patterns related to smartphone use. The proposed research model demonstrated how habitual smartphone use can lead to increased use of smartphones and further into problematic interplay between cognitive, emotional, and behavioral factors. Further, the results showed that excessive smartphone use can lead to negative consequences through cognitive-emotional preoccupation with using smartphones.

Hence, the findings of this study suggest that researchers, developers and users regarding IT should pay more attention to the processes and mechanisms that cause and inhibit problematic behaviors in order to identify and break undesired effects and consequences attributed to IT use. Theoretical perspectives that can explain behaviors beyond plans, intentions and rationality should be further explored in the context of IT use.

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APPENDIX 1 MEASUREMENT ITEMS

TABLE 11 Constructs, measurement items and sources

Construct	Adapted Item	Sources
Smartphone Habit	HAB1. Using smartphone has become automatic to me. HAB2. Using smartphone is natural to me. HAB3. Using smartphone belongs to my daily routine. HAB4. I might start using smartphone before I realize I am doing it. HAB5. It would feel weird not to use A smartphone. HAB6. Using smartphone is effortless to me. HAB7. It would require effort not to use smartphone. HBA8. When I want to use social media, smartphone is an obvious choice for me. HAB9. When I want to read news, smartphone, is an obvious choice for me.	(Verplanken & Orbell, 2003; see also Limayem et al., 2007; Tarafdar et al., 2020; Van Deursen et al., 2015)
Excessive Smartphone Use	EU1. I think the amount of time I spend using smartphone is excessive. EU2. I spend an unusually large amount of time using smartphone. EU3. I spend more time using smartphone than most other people.	(Caplan & High, 2006; see also Cao et al., 2018; Zheng & Lee, 2016)
Cognitive Preoccupation	CP1. Do you find yourself unable to stop thinking about using your smartphone? CP2. Is it hard to distract yourself from thinking about using your smartphone? CP3. Do thoughts about using your smartphone intrude into your daily activities?	(Collins & Lapp, 1992; see also Cao et al., 2018; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018)
Emotion	EM1. When you feel anxious, you crave to use your smartphone? EM2. When you feel lonely, you feel an urge to use your smartphone? EM3. When you feel bored, you feel an urge to use your smartphone? EM4. Do you ever feel so nervous that you really need to use your smartphone?	(Collins & Lapp, 1992; see also Cao et al., 2018; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018)
Cognitive-Behavioral Control	CBC1. Does the sight of smartphones make you think about limiting your use of it? CBC2. Does seeing news about smartphones stimulate concerns about the need to limit your smartphone use? CBC3. Does seeing other people using smartphones remind you of your efforts to control your smartphone use?	(Collins & Lapp, 1992; see also Cao et al., 2018; Turel & Qahri-Saremi, 2016; Turel & Qahri-Saremi, 2018)

(continues)

TABLE 11 (continues)

	CBC4. Do you ever cut back on your smartphone use in an attempt to change your smartphone habits? CBC5. Do you attempt to cut down using your smartphone? CBC6. Do feelings of guilt about too much use of your smartphone help you to control your smartphone use?	
Techno-Exhaustion	TE1. I feel drained from tasks that require me to use my smartphone. TE2. I feel tired from using my smartphone. TE3. Using a smartphone is a strain for me. TE4. I feel stressed from using my smartphone.	(Ayyagari et al., 2011; see also Cao et al., 2018; Maier et al., 2015; Steelman & Soror, 2017; Zheng & Lee, 2016)
Life Invasion	LI1. I have to be in touch with smartphone even during my vacation. LI2. I feel my personal life is being invaded by my smartphone. LI3. I have to sacrifice my vacation and weekend time to use my smartphone. LI4. I feel that I have to keep my smartphone with me, although I would not always want to.	(Ragu-Nathan et al., 2008; see also Cao et al., 2018; Ma & Turel, 2019; Tarafdar et al., 2010)
Privacy Concerns	PI1. I am concerned about my privacy on smartphones. PI2. I believe that my personal information can easily be used by marketers on smartphone applications. PI3. I feel that I have to give too much information to my smartphone applications. PI4. I feel that my smartphone collects too much data about me.	(Bright et al., 2015; see also Cao et al., 2018; Karahasanovic et al., 2009)
Perceived Stress	In the previous week… PS1. How often have you felt that you were unable to control the important things in your life? PS2. How often have you felt unconfident about your ability to handle your personal problems? PS3. How often have you felt that things were not going your way? PS4. How often have you felt difficulties were piling up so high that you could not overcome them?	(Cohen et al., 1983; see also; Turel & Bechara, 2017; Turel & Qahri-Saremi, 2018)

APPENDIX 2 SURVEY COVER LETTER

Arvoisa vastaanottaja.

Tämä kysely on osa Jyväskylän yliopistossa tehtävää pro gradu -tutkielmaa, jossa tutkitaan älypuhelimen käyttöä ja käyttötottumuksia. Tutkielman tavoitteena on selvittää, millaiset asiat vaikuttavat älypuhelimien käyttömäärään sekä millaisia seurauksia älypuhelimen käytöllä voi olla. Tutkielmaa ohjaa Janne Riekkinen.

Älypuhelimien käyttö on nykyään vaivatonta, viihdyttävää ja jopa koukuttavaa. Älypuhelimista on tullut olennainen osa jokapäiväistä elämäämme ja niitä käytetäänkin nykyään enemmän kuin koskaan aikaisemmin. Mahdolliset seuraukset älypuhelimien käytöstä ovat vielä kuitenkin monin osin tuntemattomat. Tutkimuksen onnistumiseksi on tärkeää, että mahdollisimman monet älypuhelimia eri tavoin käyttävät vastaavat kyselyyn.

Kyselyyn vastaaminen vie noin 5–10 minuuttia. Kyselyssä ei kerätä yksilöiviä henkilötietoja. Vastauksia käytetään ainoastaan tutkimuskäyttöön ja niitä säilytetään turvallisesti salasanalla suojattuna. Kyselystä saatu aineisto käsitellään tilastollisin menetelmin, eikä yksittäisen henkilön vastauksia voi erottaa tuloksista. Kyselystä saatu aineisto hävitetään asianmukaisesti viimeistään 1.4.2022. Kyselyyn vastaaminen on vapaaehtoista. Kysely on auki 1.6.2021 asti.

Kyselyssä vastaajaa pyydetään syöttämään tietoja älypuhelimen keräämästä ruutuajasta sekä avauskerroista. Kyselyyn osallistuminen edellyttää, että vastaajalla on päivittäisessä käytössä Android tai iPhone (iOS) -älypuhelin ja että tiedot ruutuajasta sekä avauskerroista ovat saatavilla. Jos tietoja ruutuajasta tai nosto-/avauskerroista ei ole saatavilla vähintään edeltävän viikon ajalta, kyselyyn osallistuminen ei ole mahdollista. Ohjeet ruutuajan ja avaus-/nostokertojen katsomiseen Android sekä iPhone -laitteille löytyvät oheisista linkeistä. Huomioi, että Samsung älypuhelimille on eri ohje, kuin muille Android älypuhelimille.

Ohjeet ruutuajan ja nostojenkertojen katsomiseen iPhone älypuhelimesta:
https://jyu-my.sharepoint.com/:b:/g/personal/kimjohke_jyu_fi/EXwz_EAPVm1DkFJGXGouS68BeX5kjMIm8rf2fUf9Nl-LrA?e=IT2rWe

Ohjeet ruutuajan ja avauskertojen katsomiseen Samsung älypuhelimesta:
https://jyu-my.sharepoint.com/:b:/g/personal/kimjohke_jyu_fi/Efv65N6GqGVKvoAV0Z7R1Q4BYWGV2tTOD8mg9lwXFDALlA?e=pSf26E

Ohjeet ruutuajan ja avauskertojen katsomiseen muista Android älypuhelimesta (esim. OnePlus, Nokia, Huawei, Xiaomi -merkkiset älypuhelimet):
https://jyu-my.sharepoint.com/:b:/g/personal/kimjohke_jyu_fi/EaWtXc1nMjlDjktZPTK_RdoBlaFIhQj-gchQNnxfO3noiA?e=SKhkaN

Pääset vastaamaan kyselyyn alla olevasta Webropol-linkistä. Kyselyyn vastaaminen onnistuu millä tahansa laitteella, mutta helpoiten se onnistuu tietokoneella.
https://link.webropolsurveys.com/S/7AE9006385A2810C

Vastauksista etukäteen kiittäen,

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