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Screen Time and Productivity: An Extension of Goal-Setting Theory to Explain Optimum Smartphone Use

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Abstract:

Over the past several years, much research has examined the negative consequences that can arise from smartphone use. To help reduce these consequences, companies have developed smartphone applications and features to enable self-monitoring behaviors. However, the mechanisms that have caused smartphone-enabled self-monitoring behaviors to emerge and the positive outcomes that might result from such behaviors have received limited scholarly attention. In this study, we ameliorate this gap by proposing a framework that highlights key antecedents and outcomes of screen-time self-monitoring success based on a smartphone-based self-monitoring intervention. Informed by a short-term longitudinal study, our results show how smartphone-based self-monitoring can enhance awareness of smartphone use and, consequently, lead to positive outcomes for users. Our findings reveal that how users perceive smartphone self-monitoring affordances, their outcome expectations, and their smartphone self-monitoring efficacy positively relate to the extent they engage in smartphone-based self-monitoring behavior. In turn, self-monitoring enhances user productivity and leads to an overall sense of contentment with achievement. Nevertheless, our findings suggest that self-monitoring fatigue negatively moderates these relationships. This study offers novel theoretical and practical insights to encourage users to use smartphones in a more regulated manner. More generally, this study contributes to the literature on self-monitoring and self-regulation in digitally enabled environments.

Keywords: Smartphone, Goal Setting, Self-regulation, Self-monitoring, Productivity, Contentment, Self-monitoring Fatigue, Screen Time, Affordance.

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1 Introduction

As a major manifestation of advances in information and communication technologies, smartphones have revolutionized the relationship between humans and digital technology. They have enabled new possibilities for social networking, gaming, shopping, and entertainment and new ways to connect with others and search for and share information. However, despite the unequivocal benefits that smartphones have created, we can also identify a dark side to their omnipresence in our lives and ever-increasing use (Lee et al., 2014b; Moqbel et al., 2022). Indeed, research has revealed that one in four children and young people have problematic smartphone use (Sohn et al., 2019). Additionally, over 60 percent of smartphone users self-report a dependence on or addiction to their devices (Statista, 2021). Research has typically linked addictive smartphone use to symptoms such as strain, intolerance, withdrawal, and relapses, which conflict with job-related tasks more than half the time (Lapointe et al., 2013; Moqbel et al., 2022). Hence, similar to other systems supporting leisure-based hedonic behaviors, such as the Internet, social media, and online games (Vaghefi et al., 2022), smartphones can create problems and lead to negative consequences for users (Brooks et al., 2017; Olson et al., 2022).

Given the significant rise in smartphone usage over the past few years, especially during the coronavirus disease of 2019 (COVID-19) pandemic (Ratan et al., 2021), research has linked smartphone use to problems in social interactions, interference with school and work, and impulse-control disorders (Chen et al., 2019; Elhai et al., 2018; Panova & Carbonell, 2018). Research has also found an association between problematic smartphone use and negative physical, technical, professional, and emotional consequences for users (Bjerre-Nielsen et al., 2020; Duke & Montag, 2017; Wolniewicz et al., 2018). For instance, Lemola et al. (2014) found that excessive smartphone use can lead to sleep disturbances and depression. Hence, researchers have given much attention to its adverse effects (Turel et al., 2021) and, more recently, to its impact on productivity (Popoola & Atiri, 2021; Singh & Dasgupta, 2021).

While research on smartphones' negative consequences has accumulated over the last decade, research on corrective behavior and interventions has emerged only recently. By corrective behaviors, we mean behaviors that focus on helping users change their less desirable behaviors for behaviors that primarily benefit them (Osatuyi & Turel, 2020). One plausible approach to overcome the negative consequences would be quitting (Qahri-Saremi et al., 2021) or taking weeklong breaks from using a device (Stieger & Lewetz, 2018). While these strategies can be effective, implementing them may lead users to lose the benefits that smartphones offer altogether (e.g., better connectivity, access to the Internet and email from anywhere, or navigation) along with its side effects. Thus, an alternative, practical approach involves optimizing smartphone use through self-regulation (Osatuyi & Turel, 2020). Such behaviors may more feasibly generate desirable outcomes without sacrificing the myriad benefits that smartphones offer.

While growing evidence shows that self-regulation predicts productive technology use (Bruhn & Wills, 2018), studies fall short in explaining *how* self-regulatory behaviors emerge and lead to positive outcomes. Likewise, the impact that self-regulation has on technology use remains up for debate (e.g., Jiang & Cameron, 2020; Ranney & Troop-Gordon, 2020). We need to address this issue since doing so could provide insights into how we could fully or partially curb the negative consequences that arise from using smartphones. We also need such research to promote ways to meaningfully use digital technology since research has frequently cited the need to understand the technology-enabled self-regulation process to develop effective interventions across disciplines (e.g., Bruhn & Wills, 2018; Chow & Luzzi, 2019; Faurholt-Jepsen et al., 2019; Jiang & Cameron, 2020).

Self-monitoring, which involves recording and tracking a behavior's intensity and frequency, represents one common way to achieve self-regulation (Turner-McGrievy et al., 2013). Research has reported self-monitoring for behavioral control to have positive effects in various contexts, such as physical activity or weight loss (Burke et al., 2011). However, to our knowledge, little research has examined smartphone self-monitoring and the factors that drive this behavior. Recent studies have revealed the importance of smartphone-based self-monitoring in different contexts, from physical health (Jiang & Cameron et al., 2020; Thornton et al., 2021) to mental health (Gatto et al., 2020; Melbye et al., 2020). Although self-monitoring cannot address all adverse effects that may result from using smartphones, behavioral sciences support self-monitoring as a practical measure to improve the extent to which users productively use smartphones (see Harris, 1986; Olson & Winchester, 2008). Still, the self-monitoring literature falls short in portraying how self-monitoring and, in particular, smartphone-based self-monitoring improves productivity. Accordingly, we first argue that examining the network of factors associated with smartphone self-monitoring and productivity has merit and can guide efforts to design and implement self-monitoring interventions. Second, despite the

supportive role that self-monitoring plays in self-regulation (Abhari et al., 2021), research on self-regulation suggests that maintaining self-monitoring comes with challenges. Therefore, we need to understand why, as individuals carry out self-monitoring over time, their willingness to control their behaviors may decrease (Baumeister, 2002; Muraven & Baumeister, 2000).

Prior studies on exercise activities have shown that, when depleted, exercise self-regulation can lead to reduced adherence to subsequent exercise activities (Martin Ginis & Bray, 2010; McAuley et al., 2011). Other studies have also reported self-regulation depletion to have comparable effects in digital environments such as mobile health (Corden et al., 2016), eHealth (Footracer, 2015), social media use (Bright et al., 2015; Dhir et al., 2019), and security compliance (Olt & Mesbah, 2019). Fatigue represents one such effect that prior research on self-regulation depletion has systematically studied (Brick et al., 2016; Pageaux et al., 2015). Psychology research has defined fatigue as a personal reluctance to continue engaging with a task or performing a certain behavior (Brown, 1994) and a subjective state of tardiness due to exhaustion (Ravindran et al., 2014). As it pertains to self-regulation, one can see fatigue as a perceptible, cognitive feeling of exhaustion caused by extended self-regulation, which can reduce how well one performs a behavior in the future (Pageaux et al., 2015). Prior IS research has used the term fatigue from technology use to explain how users may feel tired from using (mostly hedonic) technologies such as social media (e.g., due to repetitively using the same features) or overloaded from too much information and communication on social applications (Corden et al., 2016). Nonetheless, to our knowledge, little research has examined whether fatigue occurs as users self-regulate their smartphone use. We posit that it seems reasonable to expect that self-regulatory resources may become exhausted as users continue to monitor themselves, which, in turn, may cause fatigue for reasons such as cognitive overload (see Hales et al., 2016). We argue that self-monitoring fatigue would then negatively affect self-monitoring outcomes.

Taken together, we need to consider self-monitoring's positive and negative aspects in evaluating smartphone-based self-monitoring outcomes. Accordingly, in this study, we focus on self-monitoring through smartphone technology. Specifically, we address the following research question:

RQ: What are the antecedents and outcomes of smartphone self-monitoring?

To answer this question, we draw on goal-setting theory (GST) (Locke & Latham, 2002) and propose a research model that details the relationships between self-monitoring efficacy, outcome expectations, perceived affordances, and smartphone self-monitoring. We posit that smartphone self-monitoring, in turn, predicts improvements in individuals' productivity and contentment with goal achievement. We also propose that self-monitoring fatigue can moderate the effect that self-monitoring has on these outcomes. We provide support for our proposed model and hypotheses via analyzing data that we collected in a multi-wave survey that we administered to participants in a smartphone self-monitoring intervention. We found that technology's support for self-monitoring, such as Apple's embedded screen-time feature, plays as crucial a role as behavioral and cognitive factors in the smartphone use context. More generally, our findings contribute to the growing literature on strategies to overcome the negative consequences associated with technology use and suggest that an optimal intervention approach should go beyond targeting cognitive and behavioral drivers and invest in self-monitoring technology (e.g., apps and features).

This paper proceeds as follows: Section 2 provides an overview of the literature and details the theoretical foundations. We also illuminate the underlying mechanisms between personal and technological factors that contribute to self-monitoring and its outcomes. Section 3 presents our theoretical model and describes our hypotheses regarding the relationships between smartphone self-monitoring's antecedents and outcomes. In Section 4, we describe the intervention and method we used to collect and analyze the data we obtained and, in Section 5, present our results. In Section 6, we discuss our findings and the study's contributions to theory and practice. Finally, in Section 7, we conclude the paper.

2 Background

2.1 Consequences of Smartphone Use and Corrective Behaviors

Smartphones have penetrated every aspect of our daily lives (Vaghefi et al., 2017) and have meaningfully improved our personal, social, and professional activities (Loid et al., 2020). For instance, smartphone applications afford new ways to communicate with others, offer accessible learning options, and help people stay organized, safe, healthy, and informed (Gowthami & Kumar, 2016). Among their positive outcomes, smartphones can significantly enhance productivity by allowing individuals to connect and work from any place and time, which presents unparalleled productivity opportunities. However, recent IS research has

shown an inevitable association between smartphone use and negative consequences on our personal and professional lives (Benlian, 2020; Califf et al., 2020). Scholars and practitioners have raised this issue as a concern (Mazmanian, 2013; Perlow, 2012) and linked smartphone use with behaviors similar to an addiction (Soror et al., 2015; Vaghefi et al., 2017), excessive use (Billieux et al., 2015), compulsive use (Wang et al., 2019), problematic use (Wolniewicz et al., 2018), and even behavioral disorders (Lachmann et al., 2018). While nuanced differences among these behaviors exist, they all confer that smartphone use can become increasingly repetitive and even urge driven (Wang et al., 2019) to the point that addiction-like symptoms such as tolerance or withdrawal may emerge (Kurniasanti et al., 2019).

Using smartphone applications such as news, games, and social media in a problematic way can increase the likelihood that individuals form or exacerbate their preexisting mental health issues such as psychological dependence (Andreassen, 2015; Park & Lee, 2012), overload (Gao et al., 2018), technostress (Brooks et al., 2017), sleep disorders, anxiety, depression (Demirci et al., 2015; Matar Boumosleh & Jaalouk, 2017), and risky behaviors (Pivetta et al., 2019). Researchers have found this problematic use to be associated with detrimental effects on users, families and friends, organizations, and even society (Mazmanian, 2013; Vaghefi et al., 2017; Venkatesh et al., 2019). Furthermore, such problematic behavior that persists over a long period may lead to a lower quality of life and emotional well-being (Lachmann et al., 2018)¹.

In the presence of such negative consequences, many users become motivated to apply corrective behaviors in order to take control over how they use smartphones and remedy the negative consequences (Soliman & Rinta-Kahila, 2019). For instance, prior research has investigated switching an addictive application, taking occasional breaks (Hanley et al., 2019), or even quitting and uninstalling an application from a device (Vaghefi et al., 2020). While these strategies could work, they also mean that the user loses the utility that smartphone applications provide. For example, although uninstalling Facebook could temporarily benefit users, taking such measures would prohibit them from connecting and communicating with their peers and, thus, lose their access to all the information and messages exchanged on the platform. Replacing a smartphone with an older phone without the Internet can adversely affect individual productivity. Older phones may not provide easy access to the Internet and do not contain tools such as email clients and navigation applications.

Self-regulation (via self-monitoring device use in particular) represents a better strategy to help curb smartphone use (Abhari et al., 2021). As a case in point, in 2018, Apple introduced the screen time feature for iOS and advertised it as follows: “[w]ith Screen Time, you can access real-time reports showing how much time you spend on your iPhone, iPad, or iPod touch. You can also set limits for what you want to manage.” (Apple, 2018). This advertisement assumes that by self-monitoring the extent to which they use their smartphone, users can reduce negative consequences such as reduced productivity and well-being (Duke & Montag, 2017). While the assumption appears logical, we lack theoretical knowledge about self-monitoring behaviors and smartphone use. Therefore, we need more research to better understand key factors that facilitate or challenge smartphone self-monitoring to realize its intended outcomes.

2.2 Self-monitoring Behavior

While smartphone self-monitoring behaviors have received limited attention in prior research, self-monitoring is one of the most established and well-documented strategies that individuals use to regulate their behavior (Gunstone, 2013; Zimmerman et al., 1996). As an essential element of self-regulation, self-monitoring refers to paying “deliberate attention to some aspect of an individual’s behavior and recording some details of that behavior... as well as the conditions under which they occur and their immediate and long-term effects” (Burke et al., 2011, p. 93). During the last three decades (Bruhn et al., 2015), the self-monitoring literature has shown that when individuals closely monitor their behaviors and follow strict ways to track them down (e.g., using a diary or a checklist), they become better aware of the benefits and deficits of the particular actions related to that behavior (e.g., exercising, eating and diet) (Burke et al., 2011). In return, this awareness helps them to better regulate their future behaviors in light of possible gains and consequences (Schwarzer et al., 2015).

¹Scholars across disciplines such as information systems (IS), health, or psychology continue to debate the criteria needed to formally diagnose such behaviors (e.g., considering technology use as an addiction or a disorder). Nonetheless, prior research has found significant behavioral and neurological similarities between smartphone (or other technology) addiction and other behavioral addictions (Turel & Vaghefi, 2019). For instance, internet gaming disorder is included as a condition in the latest version of Diagnostic and Statistical Manual of Mental Disorders (DSM5).

Research has explained the effect of self-monitoring on users' behaviors in multiple ways. For instance, it has shown that self-monitoring 1) provides a medium for self-evaluation, 2) allows users to reflect on their past behavior (Bandura & Cervone, 1983; Schunk, 1996), 3) increases accountability and self-esteem, which, as a result, 4) improves how well they perform that behavior (van der Bij et al., 2016). Individuals with a high self-monitoring capacity can observe their behavior more objectively and adapt to their environment faster than those with a low self-monitoring capacity (Mill, 1984; Pillow et al., 2017). Those individuals also tend to interact with others and behave in a more disciplined manner. More importantly, prior research has established that individuals who have self-monitoring routines exhibit a high correspondence between their emotions, attitudes, and behaviors (e.g., Burke et al., 2009). Finally, such individuals tend to possess higher self-esteem and an internal locus of control (Day & Schleicher, 2006), which contributes to their ability to better regulate their own behavior.

Research has also recognized self-monitoring's positive outcomes as related to various self-regulatory behaviors. For instance, research has found self-monitoring to increase students' attention span, accelerate patients' recovery process, and reduce sedentary behaviors in adults or help them to regulate their diet and physical activities (Carvalho et al., 2009; Compennolle et al., 2019). Moreover, self-monitoring can positively affect behavior and productivity and, ultimately, improve performance (Ghanizadeh, 2017). For instance, in their study, Schmitz and Perels (2011) found that students who used standardized diaries as a self-monitoring tool achieved higher learning outcomes.

Although self-monitoring can contribute to helping one maintain a new behavior and achieve various positive outcomes, users cannot exert it consistently at a high level given its finite nature. Scholars have argued that one can see an individual's self-regulation as limited energy (i.e., resource) that becomes depleted over time, which leads to a state of self-regulation exhaustion or "ego depletion" (Baumeister, 2002; Baumeister & Vohs, 2016; Muraven & Baumeister, 2000). In such a state, individuals will enter a low self-regulation period until they recover these resources. Further studies have also shown that a decline in self-regulation (i.e., self-regulation fatigue) can occur due to the energy and conscious decision making required to fight temptation and craving during a self-regulatory act (Baumeister & Vohs, 2016). In the technology use context (e.g., social media use), research has linked use-related fatigue to factors such as fear of privacy invasion (Dhir et al., 2019; Xiao & Mou, 2019) and information and communication overload (Corden et al., 2016). The technostress literature suggests these stressors can have adverse effects on self-regulated technology use (Brooks et al., 2017; Salo et al., 2022) and, as a result, harm productivity (Tarafdar et al., 2007). In this study, however, we take a different approach and focus on self-monitoring fatigue and not use-related fatigue to better understand self-monitoring's limitations.

2.3 Smartphone-based Self-monitoring

While smartphone use, when out of control, can cause some negative consequences, some features and affordances (the action possibilities enabled by smartphone features) can help users regain control over their use and counterbalance the adverse effects. For example, smartphones and similar technologies can help users track their smartphone use and enhance the extent to which they can implement self-monitoring (Bruhn et al., 2016). According to cognitive and affective behavioral models, technology-enabled self-monitoring can reduce the negative consequences that arise from using smartphones. For instance, self-monitoring renders emotional self-awareness, which increases sensitivity to the negative feeling of certain behaviors and motivates behavior change (Chan et al., 2015; Jack & Miller, 2008). Regarding social media use, research has shown that usage monitoring can have a positive effect on youths' and young adults' overall well-being (e.g., by reducing anxiety and depression) (Coyne et al., 2020; Eschler et al., 2020). Also, in the smartphone use context, some studies have introduced technology-enabled self-monitoring as a potential remedy for excessive use or addictions (Compennolle et al., 2019; Okeke et al., 2018). These studies suggest that tracking and monitoring screen time can result in moderated smartphone use.

While these studies have helped explain smartphone user behaviors, we need more research on the topic for two reasons. First, existing studies do not theoretically explain the factors and conditions necessary for self-monitoring efforts to succeed. We need such knowledge given that anecdotal evidence shows that most users drop using tracking features and applications rather quickly (Kaye et al., 2020). Furthermore, knowledge about smartphone self-monitoring's potential outcomes remains at an early stage. For instance, studies have found mixed and inconclusive findings as to the effect that screen-time monitoring has on performance (i.e., they have found both an increase and decrease in performance) (e.g., see Orben, 2020). Second, the self-monitoring literature falls short in explaining self-monitoring's downsides in the smartphone use context (e.g., whether smartphone users may back away from screen-time monitoring when they

become overwhelmed with frequent alerts and notifications). We address these limitations in this study by offering a theoretically grounded and empirically validated model that explains smartphone-based self-monitoring behavior more rigorously. We draw on goal-setting theory (GST) (Locke et al., 1981) to identify the critical factors that lead to smartphone self-monitoring, which, in turn, enhances productivity and content with (goal) achievement.

3 Theoretical Framework and Hypotheses

We use GST to study smartphone self-monitoring for two reasons. First, Locke and Latham (2002) essentially created GST to formulate whether a goal-directed behavior succeeds by assessing the relationship between goal setting, motivation, goal accomplishment, and outcome achievement (Locke & Latham, 2002). In the same way, GST can explain smartphone self-monitoring behavior given that these applications allow users to set limits on their screen time (e.g., daily or weekly goals) and then track and monitor their use according to the set goals where success could mean screen time that does not exceed the goal limits. Second, researchers have used GST more broadly to explain individuals' behavior in other similar contexts with a focus on self-monitored behavior to achieve goals, such as student learning (Bloom, 2013), physical activity (Munson & Consolvo, 2012), and weight loss (Burke et al., 2011).

3.1 Goal-setting Theory

Originating from industrial-organizational psychology and Locke and Latham's (2006, 1981) work, GST argues that goals that have specific and precise details typically lead to more concrete outcomes and improved performance as compared to vague, unclear goals or abstract statements (e.g., "do the best I can!"). Many experimental studies that GST has informed have established that individuals who have set explicit goals show a higher capacity to self-regulate their behaviors toward a specific goal, which helps them to steer away from other distractions or irrelevant goals. Researchers have also found goal setting to increase individuals' enthusiasm and intrinsic motivations and, thus, to lead them to expend more energy toward achieving goal-directed tasks (Morisano et al., 2010). Furthermore, goal setting appears to improve individuals' persistence when they face difficulties, anxiety, frustrations, and negative affect (Locke & Latham, 2002).

GST has provided explanations for broad classes of factors that lead individuals to achieve goals. The first category relates to how much people believe that they can achieve important goals and tasks. Therefore, those who think they can achieve goals have a higher likelihood of doing so. Although one can consider several factors in this category such as training, experience or success, skills, or information, the goal-setting literature has widely used the term self-efficacy. Self-efficacy refers to one's confidence in own ability to act in order to achieve an intended outcome (Carberry et al., 2018). According to Locke and Latham (1990, p. 220), "self-efficacy includes all factors that could lead one to perform well at a task (e.g., adaptability, creativity, resourcefulness, perceived capacity to orchestrate complex action sequences)". Prior research has shown that self-efficacy, very much like setting goals, directly affects achieving goals and higher performance (Bandura, 1982). This effect occurs through mechanisms that strengthen goal choice (e.g., focusing on set goals rather than choices), increase commitment, and help individuals find better strategies to achieve the relevant goal.

The second category concerns outcome or performance expectations, which refer to the individuals' confidence that their effort and energy will lead to outcomes that they anticipate and the achievement of goals. Individuals who believe that their action will produce the intended results have positive outcome expectations and are more likely to act accordingly to attain them (Schunk, 1990). Prior research in psychology has shown that, while individuals can follow many choices and strategies in every situation and that these strategies may all provide some value, individuals tend to follow those that seem more likely to successfully result in the intended outcome (Betz & Hackett, 1986). While self-efficacy and outcome expectations concepts may seem similar, they address distinct constructs. More specifically, the former concept refers to one's estimate about what outcome will arise from pursuing a course of action, while the latter refers to one's confidence in one's own ability to execute actions required for an outcome (Bandura, 1991).

The third category considers the effect that the environment has on a goal-setter that enables and hinders goal attachment and a target behavior (also referred to as situational resources/constraints). For instance, when the environment makes it easy to set and follow goals or provides praises and rewards for goal attainment, people are more likely to succeed in attaining their goals (Latham & Locke, 1991). The

environment could have a limiting effect when it restrains users from setting and attaining goals or when they incur punishments for taking specific actions. According to Bandura (1997, p. 21), “[a] high sense of personal efficacy in a responsive environment that rewards valued accomplishments fosters aspirations, productive engagement in activities, and a sense of fulfillment”. To study the environment’s role in this context, we should choose context-specific variables (Hong et al., 2014) related to smartphone use. Given that smartphones now include screen time features and apps, smartphone affords several ways to help users monitor their behaviors via goal setting. We study these underexplored context-specific factors (Hong et al., 2014) through an affordance lens (Karahanna et al., 2018).

The affordances concept considers the relationship between individuals and technology and “the possibilities for goal-oriented action afforded to specified user groups by technical objects” (Markus & Silver, 200, p. 622). Researchers have used the concept in various contexts to explain technology user behaviors at both the organizational (Leonardi, 2013; Majchrzak et al., 2013) and individual (micro) analysis levels (Abhari et al., 2022; Goh et al., 2011; Vaghefi et al., 2022). In this study, we study the design affordances of smartphone screen-time monitoring options as the individual factors that contribute to one’s self-monitoring behaviors. This approach corresponds to calls in research to contextualize theoretical insights more and include technology factors to understand a phenomenon (Chatterjee et al., 2015; Chiasson et al., 2015).

Building on these theoretical foundations, we developed our hypotheses focusing on the implementation conditions that motivate self-monitoring and its outcomes in the productivity context. We limited our theoretical framework’s scope to intrinsically motivated self-monitoring behavior since intrinsically motivated individuals are more likely to experience sustained behavior change (Sheldon et al., 1997).

3.2 The Role of Self-efficacy

In this study’s context, we define smartphone self-monitoring efficacy as one’s judgment about one’s own capability to use smartphone technology for self-monitoring. This judgment can directly relate to the self-monitoring act (see Marakas et al., 1998). According to GST, to attain a set goal, individuals should perceive themselves as able to successfully take the required actions. Hence, we can expect that individuals with higher self-efficacy to succeed more at self-monitoring behaviors. Prior research has shown that self-efficacy enables more commitment toward (especially hard-to-attain) goals (Bandura et al., 1997). Individuals who possess higher self-efficacy tend to be more adaptable and resourceful in dealing with the challenges related to challenging goals (Bandura, 1982). Research has shown self-efficacy about goal attainment to determine whether individuals will initiate a behavior, how much effort they will put into it, and how long they will persist in performing it (Marcus et al., 1992). Accordingly, researchers have recognized self-efficacy’s role in several goal-setting contexts such as healthy interactions (Harrison et al., 1996), exercising (Marcus et al., 1992), binge eating control (Linardon, 2018), and career choice (Betz & Hackett, 1986).

In the technology use context, research has also shown self-efficacy to determine users’ intention to pursue different technology-related behaviors, such as performing a specific task in a digitally enabled environment (Marakas et al., 1998). Prior research has established the important role that self-efficacy plays in the initial technology use and adoption context (Compeau et al., 1999). More recently, researchers have found an association between self-efficacy and corrective technology use behaviors such as discontinuing the use of problematic social media (Vaghefi et al., 2020; Turel, 2015). For instance, Turel (2015) showed that users’ self-efficacy beliefs can predict their intentions to discontinue addictive social networking site use. In the same vein, we argue that users’ higher self-efficacy to monitor their smartphone use (which we refer to as smartphone self-monitoring efficacy henceforth) strengthens and commitment and elevates their efforts toward self-monitoring, which increases the likelihood that they will successfully monitor and achieve outcomes. Therefore, we hypothesize:

- H1:** Higher smartphone self-monitoring efficacy is associated with higher smartphone self-monitoring.

3.3 The Role of Outcome Expectations

According to GST, outcome expectation motivates individuals to work on set goals—especially goals such as self-regulation that require significant effort to maintain (Compeau et al., 1999). Existing research has identified the consequences that users expect to result from achieving a goal and its potential benefits as key denominators of behavioral change and goal attainment in many contexts (Webb & Sheeran, 2006),

such as self-monitoring (Landry, 2003) and controlling problematic behaviors (e.g., smoking) (Godding & Glasgow, 1985). Prior IS research has also shown that individuals who more favorably view gains from using a system (e.g., improved job performance or enhanced communication) have a higher tendency to adopt and use the system (Venkatesh, 2000). Similarly, expecting corrective action (such as self-monitoring) as an outcome can increase individuals' willingness to start that behavior (Bandura, 1991; Compeau et al., 1999). In our context, we expect that smartphone users who perceive that their self-monitoring efforts will have more favorable outcomes (e.g., increased productivity) are more likely to engage and then sustain their self-monitoring behavior. Therefore, we hypothesize:

H2: Higher self-monitoring outcome expectations are associated with higher smartphone self-monitoring.

3.4 The Role of Self-monitoring Affordances

While research has noted technology's role in assisting self-monitoring behavior for the past decade, the research on the potential effect that technology has on whether these efforts succeed continues to develop (Jensen et al., 2016). For example, studies provide some evidence that self-monitoring may have a positive effect on students' learning outcomes (Bedesem, 2012), weight control (Jensen et al., 2016), eating disorders (Tregarthen et al., 2015), physical activity (Ormel et al., 2018), stress management (Swendeman et al., 2018), and even their ability to self-manage psychiatric disorders (Faurholt-Jepsen et al., 2019). Overall, these studies provide a positive view on using smartphone features and applications to set goals and their significance in achieving outcomes (e.g., Patel et al., 2019). Smartphone-based interventions also appear a viable and accessible strategy to reduce screen time and work disruptions (Lubans et al., 2014). In the same vein, developers have created mobile applications and iOS and Android features to bring awareness to users about their smartphone use and its potential negative consequences (Howells et al., 2016). These applications typically include features that enable screen-time monitoring with nudging options that can help address smartphone addiction (Lee et al., 2014a).

To capture technology's effect, we extend the affordance lens to the self-monitoring context and examine the role that smartphones themselves have on self-monitoring behaviors. Unlike prior studies, we examine smartphone affordances to regulate behaviors associated with smartphone use itself rather than external activities such as monitoring diet, health indicators, or learning. Users should perceive these possibilities before their goal-directed intentions can actualize them. We argue that the perceived functional affordances provide a broader and more generalized way to view the utility that smartphone self-monitoring technology offers as compared to the features that may manifest in different forms from one application to another (see Abhari et al., 2017; Jarrahi et al., 2018; Lu & Cheng, 2013; Witt & Riley, 2014). These studies suggest the extent to which users perceive the affordances of self-monitoring functions (that their smartphone affords) as possibilities to self-monitor will positively affect their self-monitoring behaviors. Therefore, we hypothesize:

H3: Higher perceived smartphone self-monitoring affordances are associated with higher smartphone self-monitoring.

3.5 Self-monitoring Outcomes

Although smartphones have unequivocally contributed to our capacity for productivity, their ubiquity and unlimited access to the Internet, social media, and other hedonic applications has also presented a roadblock to sustainable productivity. The adverse effects on productivity from smartphone use may occur in multiple ways. First, constant interaction with these devices can add up to a significant amount of time during the day, which limits time spent on important productive tasks. Frequent interaction with smartphones (which can occur as frequently as every five minutes) can also create severe workflow disruptions (Addas & Pinsonneault, 2018). Accordingly, mounting evidence indicates that excessive smartphone use has significant deleterious effects on work productivity (Vaghefi et al., 2017) and academic performance (Samaha & Hawi, 2016). Accordingly, we expect self-monitoring to create an opportunity for users to reduce use and remedy some negative consequences (particularly regarding users' work output and productivity) as measured at a daily level (Popoola & Atiri, 2021; Singh & Dasgupta, 2021). This argument concurs with recent findings observing the positive relationship between self-monitoring and performance metrics in educational and professional settings (e.g., Bruhn & Wills, 2018; Chow & Luzzi, 2019; Meyer, 2018; Sherif et al., 2020; Wells et al., 2017). Therefore, we hypothesize:

- H4:** The higher the extent to which users monitor their own smartphone use, the more they perceive themselves as productive.

Given that self-monitoring can help individuals achieve outcomes such as improved productivity, we expect that it also contributes to their satisfaction when they achieve them (Rock, 2005). A recent study shows that those users who reported practicing self-monitoring also perceived more satisfaction with their achievement (Zhu et al., 2019). We captured this type of self-monitoring outcome via the concept contentment, which we can define as the extent to which individuals meet their wants and desires from self-monitoring (Cordaro et al., 2016). Prior research has also showed that experiencing contentment with achievement improves overall well-being, satisfaction with life, and even perceptions about life quality (Albert-Lorincz et al., 2008; Cordaro et al., 2016). Thus, we argue that contentment with achieving the set usage goal constitutes a suitable and more immediate outcome of smartphone self-monitoring behaviors, which could bring about additional positive yet distant outcomes. Therefore, we hypothesize:

- H5:** The higher the extent to which users monitor their own smartphone use, the higher their contentment with their achievement.

Although self-monitoring can directly contribute to contentment, improvements in user productivity can also contribute to it. Prior research has shown that problematic smartphone use (e.g., excessive use or addiction) typically leads to significant impairments in well-being (Moqbel et al., 2022) and productivity levels (Duke & Montag, 2017), which can lead to additional stress and reduced life satisfaction (Samaha & Hawi, 2016). At the same time, recent research provides evidence that taking corrective actions (e.g., short-term breaks from using a smartphone) can significantly improve life satisfaction (Stieger & Lewetz, 2018), perceptions about affective well-being, and quality of life (Hall et al., 2019). Hence, we argue that the productivity gains from smartphone self-monitoring can also contribute to users' overall contentment with their achievements. Therefore, we hypothesize:

- H6:** The more users perceive themselves as productive, the higher their contentment with their achievement.

3.6 The Moderating Effect of Self-monitoring Fatigue

While smartphone self-monitoring can produce positive outcomes such as improved productivity and contentment, this effect may not hold over time. As individuals carry out their self-monitoring, they will exhaust the self-regulatory resources that they need to monitor their behaviors and experience less desire to monitor their use in the future. Ego-depletion theory (Baumeister et al., 1998; Baumeister, 2003) explains this effect. This theory views the "capacity to control" as a finite resource and its strength as varying among individuals. As people exert self-control on ongoing tasks and behaviors, the self-control resource (i.e., ego) becomes depleted; in such cases, individuals have fewer resources available for subsequent self-regulatory tasks (Muraven & Baumeister, 2000). In turn, this reduction in the self-control resource increases one's vulnerability to withdraw from subsequent efforts to control a resource-demanding behavior. Nevertheless, several studies show that the extent (and pace) of self-control depletion depends on several factors such as motivation, mood, life stressors, coping skills, or even trait characteristics (Hofmann et al., 2012; Baumeister & Heatherton, 1996).

In our study's context, we expect that self-monitoring fatigue, which we define as the subjective feeling of exhaustion from self-monitoring, will interact with self-monitoring and reduces the likelihood that we will observe its positive outcomes. Accordingly, we argue that, as users exhaust their self-control resources by exerting self-monitoring over time, the resulting fatigue attenuates the effect that self-monitoring has on its outcomes. In this situation, individuals who develop more fatigue tend to apply lower quality self-monitoring (compared to when they began) and pay less attention to their smartphone use. As a result, they will achieve expected positive outcomes at a lower level (i.e., productivity and contentment with achievement). Therefore, we hypothesize:

- H7:** The higher the self-monitoring fatigue, the lower the relationship between self-monitoring and a) perceived productivity and b) contentment with achievement.

In Figure 1, we summarize the theoretical arguments that we present above. We validated this research model by implementing a longitudinal intervention that we describe in Section 4.

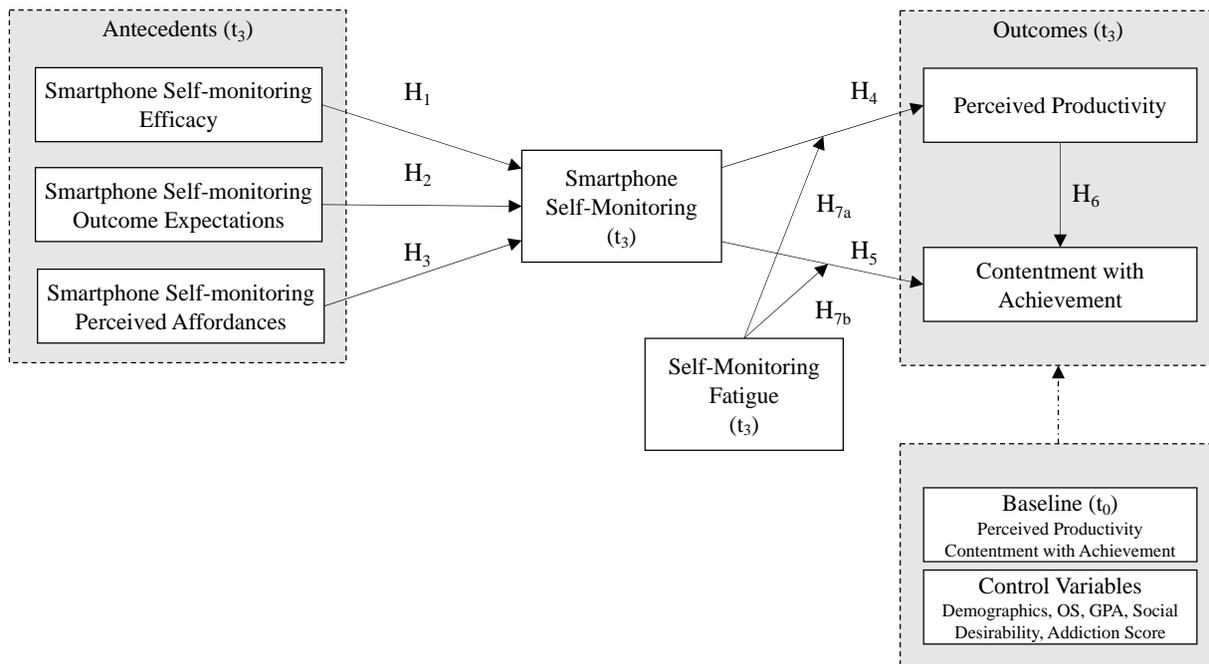


Figure 1. Research Model

4 Methodology

To validate the research model and proposed hypotheses, we designed a three-week longitudinal field study that included intervention and various surveys. We collected data from an undergraduate university student sample, which we deemed appropriate for this study for several reasons. First, prior research shows that young adults, particularly college and university students, are more susceptible to excessive smartphone use or addiction and its side effects mainly due to earlier exposure to the technology (Wang et al., 2019). Second, younger generations feature higher rates of smartphone addiction, related mental health issues (e.g., depression and anxiety), and related physical problems (Matar Boumosleh & Jaalouk, 2017). Third, students typically have a flexible schedule, inadequate supervision over their technology use (e.g., no parental control), and unrestricted access, which all contribute to their developing problematic smartphone use habits (Loiacono et al., 2018). Finally, college students highly depend on smartphone use due to their lifestyle and work style. Therefore, they are more vulnerable to addictive behavior, especially if they experience anxiety, stress, or depression (Lăzăroiu et al., 2020). Given these reasons, college students are more likely to suffer from excessive smartphone use and, at the same time, benefit from monitoring their smartphone use and bringing it back to controllable levels.

4.1 Data-collection Procedure

We collected data using a four-wave survey from three large public universities in New York, California, and Hawaii. We invited undergraduate students in business school courses from these three participating universities. We recruited all participants simultaneously and through a similar procedure (posters, class announcements, and emails). We asked them to answer a screening question regarding their interest in installing a self-monitoring mobile app to track their screen time. We used the app to assign students to treatment or control groups. We required the treatment group participants to complete four surveys and install a monitoring application (called Space, previously called BreakFree; see Appendix A). The control group encompassed the participants who did not install the app for personal or technical reasons such as battery concerns or privacy. However, they received the same surveys. We compensated all participants (control or treatment group) for their participation (we offered extra credit).

4.1.1 The Self-monitoring Tool

The Space app was the only cross-platform and free screen-time monitoring app available at the time of this study. The app also provided the same user interface with similar features for both Android and iOS.

As such, we could collect consistent and comparable data from participants on whatever phone operating system they used. The application enabled participants to set periodic smartphone usage, unlock goals (e.g., daily and weekly), and then track their usage against their set goals (see Appendix A). The participants who did not want to install the application could still participate in the study by completing the surveys. We used the data collected from this group as a control mechanism. For example, we compared the smartphone use ($t = 1.7, p = 0.01$) and addiction scores ($t = 1.02, p = 0.31$) between these two groups when we began the study and found no significant difference between them and, thus, no selection bias.

4.1.2 The Surveys

We distributed the surveys to the participants when we began the study (t_0), at the end of the first week (t_1), at the end of the second week (t_2), and, finally, at the end of the third week (t_3) (see Figure 2). In the first data-collection phase (t_0), we also asked participants to install the Space app and answer a set of baseline questions on their smartphone usage, perceived productivity, and contentment with achievement. Then, we instructed participants to upload a screenshot of the app installed on their smartphones as part of the survey. While the surveys were anonymous, we assigned a random ID to each participant and asked them to use the same ID to submit all four surveys so we could match responses to the right individual. We measured demographic variables at t_0 , which included participant gender, school year, and smartphone operating system. We measured other control variables, such as social desirability, at t_3 .

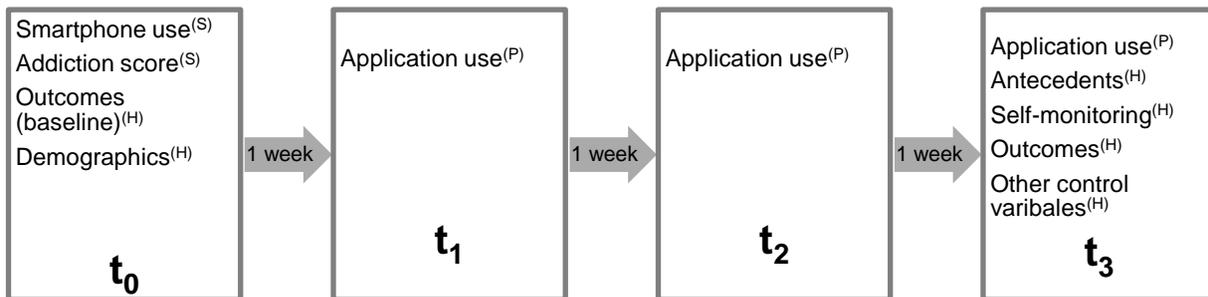


Figure 2. Survey Distribution²

While we used the t_3 survey outcome to test our model, we controlled for baseline values, perceived productivity, and contentment with achievement, which we measured at t_0 . We needed to account for these control variables as we had an interest in changes and improvements in the self-monitoring behaviors and outcomes for the users (see Kim & Malhotra, 2005). While we did not use the data that we collected during t_1 and t_2 to test the hypotheses, we asked participants to upload a screenshot of the Space app's "dashboard", which showed their mobile usage for that week (see Figure 3). We used the screenshots to verify that they continued to use the app and cross-check the usage numbers that we collected via the survey to ensure the intervention's fidelity (Chiasson et al., 2015; Williams et al., 2017). We excluded participants who failed to submit all screenshots or removed the app at any point during the study from the dataset.

4.2 Measurements

We adopted validated measurements from previous studies but made minor adjustments to them so that they made sense in our context (Duke & Montag, 2017; Gökçearsan et al., 2016; Lubans et al., 2014). Our antecedents included perceived smartphone self-monitoring efficacy (Gökçearsan et al., 2016; Jerusalem & Schwarzer, 1992), self-monitoring outcome expectations (Compeau et al., 1999), and self-monitoring affordances (Rockmann & Gewald, 2018). We measured self-monitoring with Houghton and Necks' (2002) scale and self-monitoring fatigue with Zhang et al.'s (2016) scale. The outcome variables included perceived productivity (Miller & Cardy, 2000) and contentment with achievement (Gendolla, 1998), which we measured at both t_0 and t_3 . We used demographics (age, gender, school year, location, race), smartphone operating system, grade point average (GPA), pre-intervention perceived productivity and contentment, social desirability, and the addiction score that the app calculated as control variables given that they might have

² H: The measurements we used to test hypotheses

P: The measurements we used to ensure participants used the apps

S: The measurements we used to ensure no selection bias

influenced the proposed relationships. Appendix B provides the list of items we used in this study (including items that we removed from the final survey). We initially tested and evaluated the instrument in a pilot study. We designed this pre-test to assess respondent concerns and questionnaire-related issues. We circulated the survey questionnaire among eight researchers familiar with both the study's concepts and context to solicit feedback on how we worded and presented the questions. Then, we conducted a pilot study via an online survey and collected data from 67 participants (separate from the sample). The pilot study helped to establish reliability and validity after we removed three items and adjusted five other items.

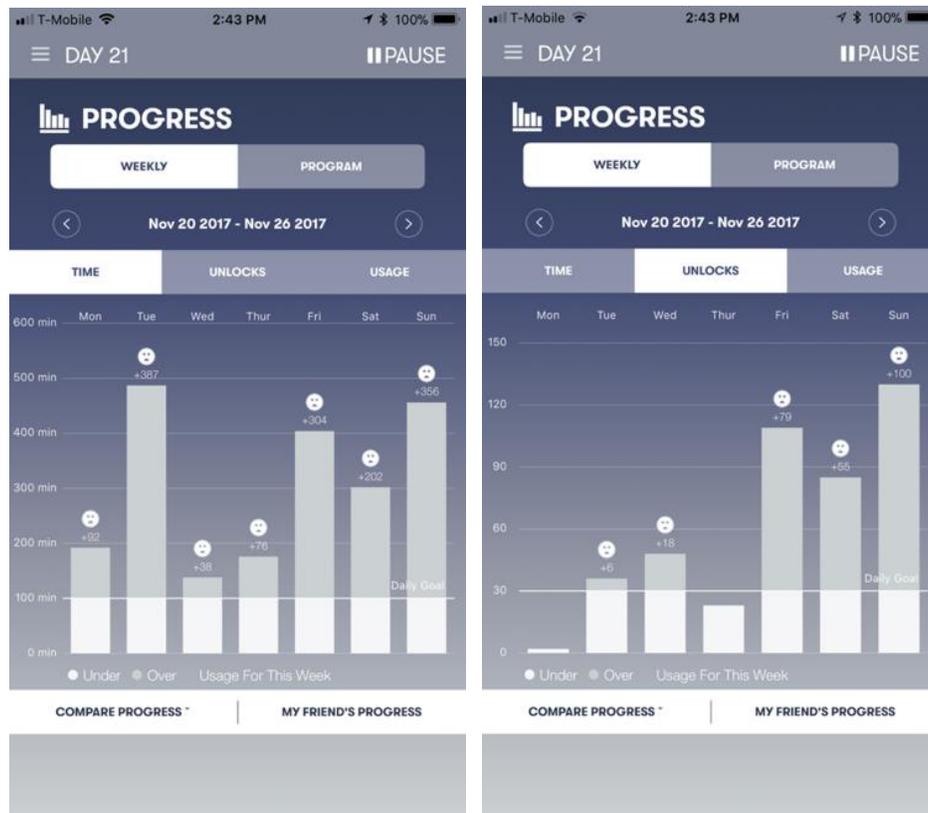


Figure 3. Images of Space App Dashboard that a Participant Submitted at the End of the Third Week

We employed the partial least squares (PLS) modeling technique and SmartPLS to assess the measurement and structural models (Ringle et al., 2015). We used PLS over other analytical techniques since we focused on developing a theory (exploration) versus testing an existing theory (confirmation) (Hair et al., 2011; Wetzels et al., 2009). Prior studies have identified PLS as a preferred method when one seeks to identify key drivers based on extending an existing structural theory (Hair et al., 2013). In developing such models, one typically seeks to maximize how much variation the independent variables (PLS) explain in the dependent variables rather than to confirm the goodness of fit between the model and data as in covariance-based structural equation modeling (Petter, 2018). PLS also offers greater efficiency in parameter estimation and prediction power in situations with inflated standard errors (e.g., due to a small sample size) (Reinartz et al., 2009).

5 Results

In total, 469 participants joined the treatment group and submitted their responses at t_0 . From this sample, we removed 138 participants due to incomplete responses (91) or missing screenshots or surveys in t_1 or t_2 (47), which left 331 usable responses for the analysis (a ~70% participation rate). We considered this participation rate acceptable given the multiple data-collection phases and the study's voluntary nature with no monetary compensation. Our sample contained 59 percent males and 40 percent females (the rest did not wish to disclose their gender). On average, they were 22 years old (i.e., ranged from 18 to 29 years old). As for their study year in university, we identified one percent in their first year, 31 percent in their second year, 31 percent in their third year, and 18 percent in their fourth year. In terms of achieving self-monitoring

goals, 14 percent reported “fully achieved”, 21 percent “mostly achieved”, 21 percent “half achieved”, 27 percent “mostly not achieved”, and 17 percent “not achieved at all”.

5.1 Preliminary Analysis

After the initial screening, we validated the measurement instrument. Evaluating reflective constructs involved testing construct reliability (item reliability and internal consistency), construct factorability, and construct validity (discrimination validity). As we report in Appendix C, all other measurement items had loadings that exceeded 0.70, which indicates acceptable item reliability. Cronbach’s alpha and the composite reliability for all constructed also exceeded 0.70 (Table 1), which indicates adequate internal consistency among the items that measured each construct (Hair et al., 2011). All average variance extracted (AVE) values exceeded 0.50, which provides evidence for adequate convergent validity (Hair et al., 2011). Further, all the pathological VIFs that resulted from the full collinearity test did not exceed 5.0 (1.0 to 3.2).

Table 1. Construct Reliability and Validity

Construct	a	CR	AVE
Smartphone self-monitoring perceived affordances	0.87	0.91	0.73
Smartphone self-monitoring outcome expectations	0.75	0.85	0.66
Smartphone self-monitoring efficacy	0.90	0.93	0.78
Smartphone self-monitoring	0.83	0.89	0.66
Self-Monitoring fatigue	0.87	0.92	0.79
Perceived productivity	0.90	0.93	0.71
Contentment with achievement	0.83	0.92	0.85

Table 2. Discriminant Validity

Construct	PSA	SOE	SSE	SLM	SMF	PP	CWA
Smartphone self-monitoring perceived affordances	0.85						
Smartphone self-monitoring outcome expectations	0.59	0.81					
Smartphone self-monitoring efficacy	0.42	0.42	0.88				
Smartphone self-monitoring	0.54	0.49	0.46	0.82			
Self-monitoring fatigue	-0.04	-0.07	-0.1	-0.04	0.89		
Perceived productivity	0.31	0.27	0.45	0.39	0.09	0.84	
Contentment with achievement	0.41	0.38	0.53	0.58	-0.01	0.76	0.92

PSA: smartphone self-monitoring perceived affordances, SOE: smartphone self-monitoring outcome expectations, SSE: smartphone self-monitoring efficacy, SLM: smartphone self-monitoring, SMF: self-monitoring fatigue, PP: perceived productivity, and CWA: contentment with achievement.

Additionally, each item loaded more highly on its construct compared to other constructs, which indicates discriminant validity. As Table 2 shows, the AVE of each reflective construct was also higher than the construct’s highest squared correlation with any other construct. The heterotrait-monotrait (HTMT) ratio of correlations also did not exceed 0.90, which indicates discriminant validity (Henseler et al., 2014). Moreover, we tested for common method bias using a full collinearity assessment (i.e., vertical and lateral). The test indicated that our study lacked common method bias since all the pathological VIFs resulting from the full collinearity test did not exceed the 3.3 recommended threshold (Kock, 2015). Therefore, we did not find evidence for significant common method variance.

5.2 Model Testing

We tested our hypotheses with control variables that could have impacted our model, namely, demographics, social desirability, and a priori productivity and contentment (baseline values measured at

t₀). To test the model, we examined how significantly the antecedents directly affected self-monitoring. We found an association between higher smartphone self-monitoring efficacy and higher self-monitoring (H1: $\beta = 0.24, p < 0.001$). We also found that self-monitoring outcome expectations had a significant positive impact on self-monitoring (H2: $\beta = 0.20, p < 0.001$) and a positive association between perceived self-monitoring affordances and self-monitoring (H3: $\beta = 0.32, p < 0.001$). Regarding the outcomes, we found that self-monitoring behavior had a positive effect on both self-monitoring outcomes, perceived productivity (H4: $\beta = 0.30, p < 0.001$), and contentment with achievement (H5: $\beta = 0.33, p < 0.001$) when controlled for their *t*₀ baseline values. In addition, our data analysis supported the relationship between perceived productivity and contentment with achievement (H6: $\beta = 0.62, p < .001$). Next, we tested the moderating effect that self-monitoring fatigue had on the effect that smartphone self-monitoring had on perceived productivity and contentment with achievement and found support for the former relationship (H7a: $\beta = -0.1, p < 0.01$) but not for the latter (H7b: $\beta = -0.05, p = 0.198$).

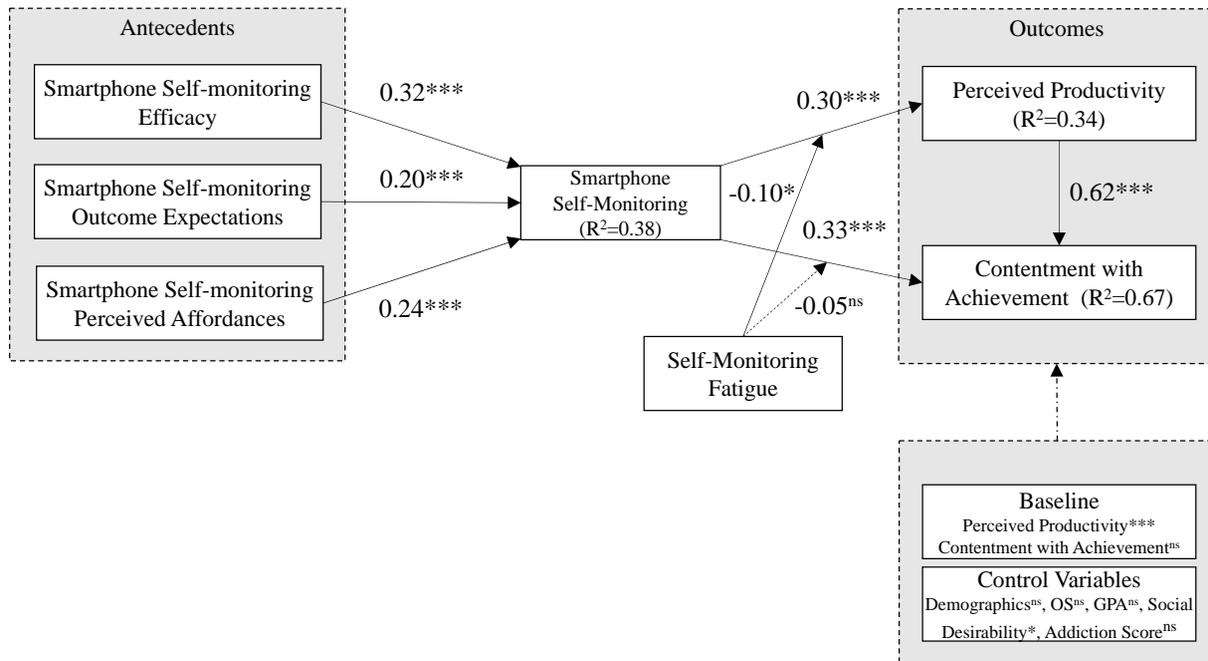


Figure 4. The Structural Model Test Results

Table 3. Path Coefficients and Significance

Hypothesis	β	t	R ²	Q ²
H1: SSE → SLM	0.24	4.59***	0.38	0.24
H2: SOE → SLM	0.20	3.42***		
H3: PSA → SLM	0.32	5.26***		
H4: SLM → PP	0.30	5.43***	0.34	0.23
H7a SLM X SMF → PP	-0.10	2.17*		
H5: SLM → CWA	0.33	7.52***	0.67	0.54
H6: PP → CWA	0.62	16.88***		
H7a SLM X SMF → CWA	-0.05	1.71 ^{ns}		

SSE: smartphone self-monitoring efficacy, SLM: smartphone self-monitoring, SOE: smartphone self-monitoring outcome expectations, PSA: smartphone self-monitoring perceived affordances, PP: perceived productivity, SMF: self-monitoring fatigue, and CWA: contentment with achievement.
 B = path coefficients, R² = determination coefficient, Q² = predictive relevance (calculated by blindfolding), ns: not significant.
 * p < 0.05, ** p < 0.01, *** p < 0.001.

Overall, we found support for all hypotheses except H7b (see Table 3). The variables accounted for 38 percent of the variance in smartphone self-monitoring, 34 percent in perceived productivity, and 67 percent in contentment with achievement in the presence of the control variables. The control variables had no

significant effect on the dependent variables except in two cases: 1) baseline perceived productivity had a significant effect on perceived productivity ($\beta = 0.30$, $p < 0.001$) and social desirability had a significant effect on contentment with achievement ($\beta = -0.10$, $p < 0.05$).

While we did not hypothesize about it, our model suggests that self-monitoring antecedents have an indirect effect on its outcomes. Hence, we tested the indirect effect that the antecedents had on perceived productivity and contentment with achievement via self-monitoring by using the bootstrapping method (Preacher & Hayes, 2008). We used this approach rather than Baron and Kenny's method or the traditional Sobel's test because it has better explanatory power and does not violate normality assumptions, especially with small sample sizes (Hayes, 2013; Preacher & Hayes, 2008; Rucker et al., 2011). With this approach, we could also directly measure the indirect effect in the bootstrapping method rather than merely infer that it existed or not through various tests. We obtained the 95 percent confidence interval of the indirect effects with 5,000 bootstraps. The findings showed the significant but modest indirect effect that the antecedents had on perceived productivity. Perceived self-monitoring affordances had a stronger indirect effect on perceived productivity ($\beta = 0.06$, $p < 0.01$, CI: 0.01—0.10) than self-monitoring outcome expectations ($\beta = 0.04$, $p < 0.05$, CI: 0.01—0.07) and smartphone self-monitoring efficacy had on perceived productivity ($\beta = 0.05$, $p < 0.05$, CI: 0.01—0.09). The antecedents, smartphone self-monitoring efficacy ($\beta = 0.09$, $p < .001$, CI: 0.04—0.13), self-monitoring outcome expectations ($\beta = 0.07$, $p < 0.01$, CI: 0.03—0.12), and perceived self-monitoring affordances ($\beta = 0.12$, $p < 0.001$, CI: 0.06—0.15), also had a significant indirect effect on contentment with achievement.

6 Discussion

In this study, we identify and test the key antecedents and outcomes of smartphone-enabled self-monitoring behavior. We identified smartphone self-monitoring perceived affordances, outcome expectations, and self-efficacy as the main antecedents of effective smartphone use self-monitoring. As expected, self-monitoring appears necessary to encourage individuals to use smartphones in an optimized way. Our results also suggest that users who expect greater outcomes from self-monitoring are more likely to monitor their smartphone use. Additionally, we argue that we can expect users to more highly engage in self-monitoring when they perceive more action possibilities with self-monitoring technology (e.g., the Space app we used in our intervention). One can enable these action possibilities through features such as screen-time recording, goal setting, usage reporting, usage dashboards, and usage alerts.

While we grounded our model in the GST (Rickard et al., 2016; Schwarzer et al., 2015; Shapiro & Schwartz, 2011), we propose a parsimonious model to predict smartphone-based self-monitoring behavior and its outcomes. Our results indicate that an increase in the extent to which users monitor their own smartphone usage leads to improvements in (perceived) productivity and contentment with achievement. Our findings support prior research that has looked at the effect that smartphones have on users' output and productivity (Duke & Montag, 2017). We note that self-monitoring smartphone use does not necessarily translate to "less use" but rather "more productive use" in our context here (we observed less than a 20 percent change in smartphone use in both directions). Therefore, our findings lend support to understanding the mechanisms through which smartphone use can be more productive. For instance, our study promotes self-initiated interventions through screen-time optimizations rather than discontinued smartphone use to avoid its negative consequences (Vaghefi et al., 2020).

Lastly, the results support that self-monitoring fatigue weakens the effect that self-monitoring has on productivity. As such, it seems that individuals need to manage fatigue in designing behavioral interventions due to the possible diminishing effect. However, this negative effect did not significantly moderate the relationship between smartphone self-monitoring and contentment with achievement. We found a partial link between content and user satisfaction with overcoming a challenge or responding to a trigger or feedback (e.g., Hanson, 2016). Accordingly, self-monitoring fatigue does not necessarily weaken the effect that self-monitoring has on contentment with achievement.

6.1 Theoretical Contributions

With this study, we make four notable contributions. First, we contribute to the emerging scholarly research on the positive and negative (aka bright vs. dark) aspects of technology use (smartphone use in particular) (Moqbel et al., 2022). We extend this literature by establishing smartphone self-monitoring as a viable mechanism to prevent the deleterious effects that uncontrolled use has on individuals' personal, social, and professional lives (Vaghefi et al., 2022; Soror et al., 2015). Prior research has examined various ways to

correct problematic behaviors (including an addiction), such as permanent or temporary discontinuance (Soliman & Rinta-Kahila, 2019). Although these strategies could be effective, self-monitoring appears to be a more realistic and sustainable approach given smartphones' ubiquity and their penetration into every aspect of life. In addition, we can consider self-monitoring a proactive approach (compared to quitting after one forms an addiction). In this way, it can allow users to take advantage of the smartphone's benefits while ensuring productivity and contentment with achievement. Some recent studies have paid attention to technology-based self-monitoring's positive outcomes. For instance, a recent eight-year study found that self-monitoring social media use positively affects overall health and reduces anxiety and depression (Coyne et al., 2020). Another study found that monitoring and reducing smartphone use by one hour each day can have long-term positive effects on individuals' well-being and help them establish healthier lifestyles (Brailovskaia et al., 2022). We extend these findings by establishing self-smartphone monitoring as a valid and effective strategy to curb (at least some) the negative consequences that arise from using smartphones.

Second, we enhance the current theoretical self-monitoring knowledge by theorizing about the antecedents to smartphone self-monitoring. Specifically, we used GST to demonstrate that outcomes expectation and self-efficacy play a critical role in self-monitoring. Without high expectations, users may perceive self-monitoring as a trivial rather than meaningful practice. Likewise, if users believe that they do not have the ability or competency to self-monitor, they may not appropriately respond to self-monitoring interventions. Moreover, changes in smartphone users' behavior can be attributed not only to the users' potential to envision their capability and expected outcomes but also to the self-monitoring capability of a smartphone that is now available to them. This finding complements prior studies that have solely focused on personal and behavioral traits (Barrick et al., 2005) and that disregarded the role that technology (affordances) plays in enabling better self-monitoring.

Third, our results extend existing knowledge on the potentially positive outcomes that result from monitoring smartphone use. While prior studies have mainly focused on controlling excessive use to minimize negative consequences (Chen et al., 2019; Elhai et al., 2018; Panova & Carbonell, 2018), we evaluated productivity and introduced a concept called contentment with achievement as a higher-order outcome. While this construct conceptually overlaps with user satisfaction (see Sultan et al., 2020), we can consider it an important factor that predicts mental health. Contentment and productivity can also help overcome the limitations that arise when using the productivity scale as the only performance measure.

Lastly, we introduced and examined self-monitoring fatigue, which increases as self-monitoring efforts go on and extend, as a moderating factor that weakens the positive relationship between self-monitoring and its outcomes. Our findings suggest that smartphone-supported self-monitoring interventions may deplete users' cognitive resources for self-monitoring and control (e.g., by frequent notification signaling excessive use) and, consequently, lead to a mental lassitude that prevents them from fully benefiting from self-monitoring efforts. This mental state can limit the likelihood that they will use the device productively. Our findings support the assertion that one can use the ego-depletion theory (Muraven & Baumeister, 2020) to understand self-monitoring technology and develop strategies to monitor and respond to fatigue.

6.2 Practical Implications

In addition to theoretical contributions, we also make important practical implications toward user-driven design in the mental health and wellness context (Djamasbi & Strong, 2019; Wilson & Djamasbi, 2015). First, we shed light on the important role that technology-enabled interventions play in supporting users' productivity. Practitioners can use the mechanisms identified through the antecedents we studied to assess and support self-monitoring and realize its outcomes. Our findings suggest that one needs to identify users with low self-monitoring efficacy and outcome expectations for such behavioral interventions to succeed. Thus, users may be more open to behavioral intervention when they initially receive sufficient support, training, and encouragement. The contributions that this study offers have greater importance for workforce development as more digital natives enter the workforce. For example, this study presents a considerable opportunity for educators and employers to intervene in obstructive smartphone use and, ultimately, impact productivity and mental health.

Second, this study supports and clarifies the positive relationship between monitored smartphone use and productivity. Our findings suggest that the first step to increasing productivity involves tracking the time users spend on their smartphones and presenting it to them in a meaningful but not exhausting and overwhelming way. This suggestion supports mobile operating system developers' decision to provide a screen-time report as a default system capability since 2018. These applications can offer additional self-monitoring

affordances that sustainable self-monitoring behaviors require. Our work also supports “quantified self-solutions” since they may lead to healthier behaviors by helping individuals consciously scrutinize ingrained, undesirable habits beyond smartphone use context (see Bajracharya et al., 2019). Hence, we encourage researchers to explore such generalizations in other contexts.

Third, this study views self-monitoring behavior in digital environments in a practical manner. In this way, it can help one design more effective self-monitoring applications in general and in other problematic hedonic technologies (e.g., online games and social media). For instance, system developers can embed features that remind users about their efficiency in achieving positive outcomes through self-monitoring. Our study confirms that such support constitutes an essential ingredient for any self-monitoring intervention that focuses on changing behavior. Otherwise, self-monitoring affordances through features such as screen time reports would not be enough to encourage self-monitoring, much less improve productivity.

Lastly, to ensure behavior change, users must accept and pursue interventions through technology for some time to warrant a change in habits. The negative effect of self-monitoring fatigue suggests that users may ignore and stop feedback and notifications after initial use. Therefore, such interventions require methods to maintain engagement with self-monitoring technology over time to succeed. Practical strategies to control self-monitoring fatigue and, therefore, improve self-monitoring outcomes include enhancing usage-tracking features, optimizing notification frequency, customizing reports, and personalized feedback.

6.3 Limitations and Future Research Avenues

Similar to most prior studies in this domain, we primarily used self-reported survey data, which limits our ability to claim causality without further investigation. While our findings concur with the literature, we cannot speak with confidence to the possibility that self-monitoring caused outcomes or that self-monitoring resulted from the introduced antecedents. For example, individuals with higher productivity may tend to self-regulate their smartphone use, or self-monitoring may have a reciprocal relationship with self-monitoring efficacy. Therefore, future research can address this limitation by validating our model in a more controlled environment and with experiments. An experimental design would allow researchers to account for other usage factors such as use type and frequency. Qualitative studies can also offer a better explanation for what motivates or hinders self-monitoring in the first place, such as interest, excitement, and confidence in such behavior or anxiety, stress, and other personal concerns. Moreover, longitudinal studies would be instrumental in exploring self-monitoring’s effects over time, especially in examining the dynamic effect of self-monitoring fatigue.

We advise some caution in generalizing our results to the larger population or another context due to limitations in sampling. We focus on sample groups that skew toward young, educated, and tech-savvy individuals. We collected data from college students in the US and, therefore, the results might not represent the general public. However, we checked whether self-monitoring was uniform within and across research sites and student groups (e.g., age, gender) to support the extent to which the findings transfer to the general student population. The results suggest that self-monitoring did not differ across demographic groups. We also used a longitudinal survey to control for the baseline values and tested for common method bias to ensure our results’ validity. Moreover, our intervention relied on one specific application (Space) and a specific self-monitoring mechanism (screen-time monitoring). Therefore, researchers need to examine other tools and technologies in the future.

Future studies could also investigate different technological interventions such as native features or embedded reporting and nudging functions in applications that users may heavily use, such as social network sites or online games. We also encourage future research to consider the technological factors that inhibit self-monitoring, such as battery power and privacy concerns, in addition to other cognitive and behavioral challenges that factors beyond fatigue cause (e.g., stress or technostress). Our study also opens new research avenues for developing and testing new technology-enabled self-monitoring interventions in light of their limitations. For example, future research could extend the principles that we establish in this study to investigate other mechanisms such as mindfulness practices, reflectiveness, gamification, and social interventions that may affect self-monitoring (Klase et al., 2022; Loiacono et al., 2018; Thatcher et al., 2019). More importantly, the long-term effect that self-monitoring has on productivity remains unclear. Future research should provide additional evidence to support that self-monitoring leads to *lasting* behavior change beyond the three-week duration that we considered. Also, scholars have not yet examined whether individuals can use episodic self-monitoring for sustainable habit change. Hence, we recommend researchers conduct additional longitudinal studies since we know little about factors that facilitate individuals to use self-monitoring technology in a sustained manner.

We should also acknowledge that self-monitoring by itself cannot prevent problematic behaviors or motivate positive changes. Hence, researchers should also investigate self-monitoring along with other external reward and supporting mechanisms. They could also investigate self-monitoring technologies by looking at user motivations, goals, capabilities, perception of usefulness, and data privacy. Likewise, future research needs to study what effect different self-monitoring features such as report and notification timing, design, frequency, and modality has on smartphone addiction and smartphone use in general.

7 Conclusion

Although research on self-monitoring continues to develop in mental health and psychology research, the IS and HCI literatures contain little theoretical and empirical research on the topic. In this study, we focused on self-monitoring via smartphones and unearthed some key mechanisms that underlie self-monitoring success. We identified smartphone self-monitoring's main antecedents (smartphone self-monitoring perceived affordances, smartphone self-monitoring outcome expectations, and smartphone self-monitoring efficacy) and its outcomes (productivity and contentment with achievement). We also shed light on the discouraging effect that self-monitoring fatigue has on whether individuals can realize self-monitoring strategies' full potential. Our study contributes to the emerging literature on productive and mindful smartphone use, and paves the way for future research and intervention programs to overcome excessive smartphone use or addiction.

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Appendix A: Space App

The Space app offers a personalized behavior-change environment that helps users monitor how they use their smartphones and reflect on how the use affects their lives. The app focuses on helping individuals find their phone-life balance through a conscious choice rather than a habit. The application does not focus on reducing screen time per se. Rather, it helps smartphone users exert control over their devices and discover their digital balance. To do so, it allows users to set goals and monitor their smartphone use (Figure A1 left), track their daily progress and benchmark performance against other Space users (Figure A1 middle), and use a toolkit and collect achievement badges (Figure A1 right). For more information, see the app website at <https://findyourphonelifebalance.com>.

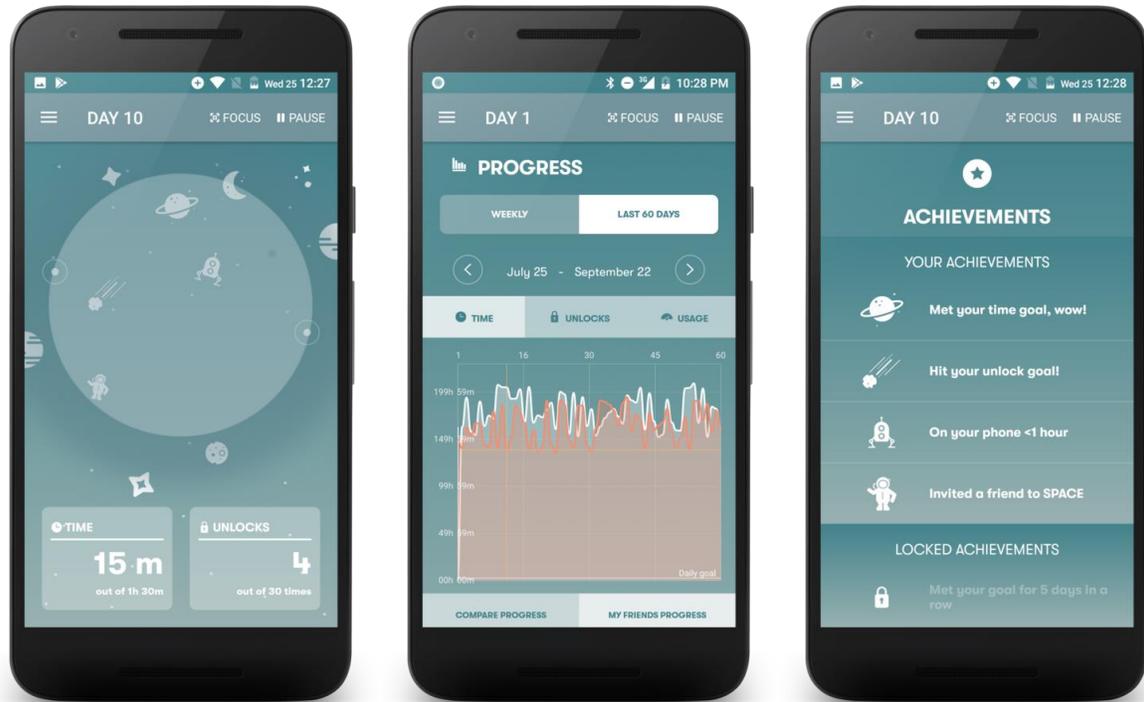


Figure A1. Set Goals (L), Track/Compare Progress (M), Achievements (R)

Appendix B: Survey Items

Table B1. Survey Items

Construct	Items*
Self-monitoring self-efficacy Gökçearsan et al. (2016), Jerusalem & Schwarzer (1992)	Using the Breakfree** app installed on my smartphone, I am: <ul style="list-style-type: none"> • Confident about the ability to manage smartphone usage • Self-assured about capabilities to control smartphone usage • Able to watch my smartphone usage carefully • Able to succeed in managing smartphone usage
Self-monitoring outcome expectations Compeau et al. (1999)	Using the Breakfree app would: <ul style="list-style-type: none"> • Enhance my effectiveness by managing smartphone usage • Improve my performance by regulating smartphone usage • Help me manage time by monitoring smartphone usage
Self-monitoring perceived affordances Rockmann & Gewald (2018)	Over the last 7 days, the Breakfree app has enabled me to: <ul style="list-style-type: none"> • Keep the history of smartphone usage • Record smartphone usage • Monitor smartphone usage • Get feedback on smartphone usage
Smartphone self-monitoring Houghton & Necks (2002)	Over the last 7 days, by using the Breakfree app: <ul style="list-style-type: none"> • I could attend to aspects of my smartphone usage behavior • I was able to watch my smartphone usage carefully • I could monitor whether I have achieved the smartphone usage goal that I set • I could keep track of my progress toward my smartphone usage goal.
Self-monitoring fatigue Zhang et al. (2016)	Over the last 7 days, how did you respond to the Breakfree app alerts? <ul style="list-style-type: none"> • I became tired of the (self-monitoring) alerts • I become wearisome of the alerts • I lost concern about the alerts • I stopped paying attention to the alerts
Perceived productivity Miller & Cardy (2000)	Over the last 7 days: <ul style="list-style-type: none"> • I was effective in managing tasks • I was efficient in performing tasks • I was satisfied with the quality of work • I felt in control of productivity • Overall, I was productive in my work (or study)
Contentment with achievement Gendolla (1998)	Over the last 7 days, I felt satisfied with: <ul style="list-style-type: none"> • Accomplishing what had planned to accomplish • Achieving the smartphone usage goal
* Items removed: Self-monitoring self-efficacy: "I am able to set a smartphone usage goal that is attainable". Self-monitoring outcome expectations: "Using the Breakfree app would be useful in managing my smartphone usage" Self-monitoring: "I could evaluate my smartphone usage behavior in light of the goal to be achieved" and "I could compare my smartphone usage level against my personal goal" Fatigue: "I ignored the alerts" Productivity: "I accomplished what I had planned to accomplish" ** Breakfree was the former name of the Space app.	

Appendix C: Item Loadings

Table C1. Item Loadings*

Items	PSA	SOE	SSE	SLM	SMF	PP	CWA
PSA1	0.89						
PSA2	0.87						
PSA3	0.83						
PSA4	0.82						
SOE1		0.77					
SOE2		0.83					
SOE3		0.83					
SSE1			0.89				
SSE2			0.9				
SSE3			0.87				
SSE4			0.86				
SLM1				0.72			
SLM2				0.83			
SLM3				0.83			
SLM4				0.87			
SMF1					0.78		
SMF2					0.93		
SMF3					0.93		
PAP1						0.85	
PAP2						0.84	
PAP3						0.85	
PAP4						0.84	
PAP5						0.85	
CWA1							0.94
CWA2							0.90

PSA: smartphone self-monitoring perceived affordances; SOE: smartphone self-monitoring outcome expectations; SSE: smartphone self-monitoring efficacy; SLM: smartphone self-monitoring; SMF: self-monitoring fatigue; PP: perceived productivity; and CWA: contentment with achievement.
* We do not show item loadings less than 0.4 for better readability.

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