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Reflective smartphone disengagement: Conceptualization, measurement, and validation

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ABSTRACT

The present paper develops a new concept, called Reflective Smartphone Disengagement (RSD), defined as individuals' deliberate efforts to control and restrict smartphone use. Based on the reflective-impulsive model, we examined the RSD concept in four studies, using cross-sectional data of adolescents (Study 1, $N = 453$, Study 3, $N = 760$) and adults (Study 4, $N = 672$), as well as panel data of adults (Study 2, $N = 461$). In Study 1, findings from exploratory and confirmatory factor analyses supported the one-dimensionality of the RSD scale. In Study 2, we found evidence for high test–retest reliability as well as discriminant validity, and in terms of predictive validity, RSD negatively predicted excessive smartphone use, information overload, and the social availability norm over time. Study 3 demonstrated convergent validity with a negative relationship with trait nomophobia and a positive one with trait self-reflection. Study 4 confirms the structural validity of a shorter version of the scale. We discuss avenues for future research and broader implications of the RSD concept for the field.

Smartphones have become permanent companions in our everyday lives. The resulting constant connectivity oftentimes ends up in the dependent and unconscious immersion with the smartphone, both in public and in private spaces, in work contexts and in the intimate sphere, making the smartphone the major vehicle for news and social media use (e.g., Bayer, Dal Cin, Campbell, & Panek, 2016). In this context, an emerging trend of individuals' disconnection from smartphones, popularly called digital detoxing, can be witnessed (Sutton, 2017). That is, the number of people who decide to consciously monitor or reduce their smartphone use is on the rise (e.g., Russo, Ollier-Malaterre, & Morandin, 2019).

Although some studies have taken into account the role of self-regulation in the context of smartphone use (e.g., Schnauber--Stockmann, Meier, & Reinecke, 2018), most research to date focused on the *compulsive dimension* of smartphone use, characterized by a lack of control (e.g., Bayer et al., 2016). This dimension partially refers to concepts such as compulsive mobile phone use (Lee, Chang, Lin, & Cheng, 2014), excessive mobile phone use (Knop, Hefner, Schmitt, & Vorderer, 2015), or mobile phone addiction (Kwon et al., 2013). These excessive forms of use are typically defined as "high cognitive and behavioral salience of the mobile phone that can conflict with other important activities" (Hefner, Knop, Schmitt, & Vorderer, 2019, p. 82) and have been found to increase negative outcomes such as stress among smartphone users (Lee et al., 2014; Thomée, Härenstam, & Hagberg, 2011).

However, the notion of disengagement from the smartphone, or what Strack and Deutsch (2004) have called the *reflective dimension,* has been widely neglected thus far. The reflective dimension is not simply the opposite of the impulsive dimension, by contrast, it relates to completely different antecedents and outcomes. In line with the notion of a reflective system, Kolb, Caza, and Collins (2012, p. 271) emphasized that "further research is needed in terms of developing metrics, but also in order to understand the role of human agency in terms of disconnecting". By the same token, Tran, Yang, Davis, and Hiniker (2019) suggested that one important factor that can end compulsive phone involvement is disengagement. And such disengagement can be defined as a reflective process. Russo et al. (2019) argue that decisions to disengage from smartphones are based on the individuals' intuitive judgements of appropriateness. For example, research on phubbing—situations of ignoring others while using smartphones during conversations—has indicated that individuals perceive constant smartphone use as socially acceptable behavior, because they experience

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phubbing from others and perform their own phubbing behaviors (Chotpitayasunondh & Douglas, 2016). Such norms point to the need for change in perceived normative behaviors surrounding smartphone use. Main implications stemming from phubbing research highlight self-control of smartphone use and suggest imposing appropriate rules to help control phubbing and excessive smartphone use (Chatterjee, 2020).

Against this background, the present study develops a new concept, called *Reflective Smartphone Disengagement* (RSD), defined as individuals' deliberate efforts to control and restrict smartphone use (Baumeister, 2007). Closely related to the theoretical concept of digital well-being that focuses on dynamic and momentary experiences of finding optimal balance between mobile connectivity and disconnectivity (Vanden Abeele, 2020), we aim to empirically demonstrate the notion of smartphone disconnection. As we will detail below, the concept of RSD opens up a new perspective in empirical research on mobile communication by shifting scholarly attention away from the compulsive dimension of smartphone use, in order to better understand the hitherto ignored importance of reflecting on and restricting mobile devices. In the empirical parts of this paper, we propose a new measurement scale that can be used in survey and experimental research, the RSD scale. We demonstrate that RSD is a one-dimensional construct that can be measured reliably, that is significantly distinct from excessive smartphone use, and we provide evidence on the predictive, and convergent validity of the concept. Finally, we outline some avenues for future research and discuss broader implications for the field.

1. Theoretical background

1.1. The reflective-impulsive model

One prominent theory to explain behavioral decision processes is the reflective-impulsive model (RIM). The RIM is situated in the dual-processes paradigm, which proposes that there are two basic modes of human information processing. While the exact terminology to describe the aspects of the two types of processing differs between the theories following this paradigm, all models distinguish between a controlled (or systematic/central) and an automatic (or heuristic/peripheral) processing mode (see Strack & Deutsch, 2004 for an overview). Specifically, the RIM postulates that social behavior is determined by two parallel and interacting systems: the *reflective* and the *impulsive system* (Strack & Deutsch, 2004). The reflective system operates on a cognitive level and refers to knowledge-based decisions and reasoned attitudes (Strack & Deutsch, 2004), restraint standards (Hofmann, Friese, & Strack, 2009), thoughtful evaluation and planned behavior (Schnauber-Stockmann et al., 2018), as well as self-control (Strack & Deutsch, 2004). In contrast, the impulsive system encompasses affective reactions, automatic behavior, and habits (Hofmann et al., 2009; Schnauber-Stockmann et al., 2018; Strack & Deutsch, 2004; Vohs, 2006). When being confronted with an impetus from the environment (in our case: input from smartphones), individuals experience an inner conflict between the two systems: the impulse toward the impetus (i.e., *impulsive*) versus the motivation to restrain from it (i.e., *reflective*) (Hofmann et al., 2009). In such a situation, various behavioral clusters proposing different actions are activated at the same time, whereas actions of only one of the two systems can be more influential (Hofmann et al., 2009).

Which system ends up being more prominent, depends on the strength of the behavioral clusters, on situational and/or dispositional factors, and especially on self-regulatory resources (Bandura, 1991; Strack & Deutsch, 2004; Vohs, 2006). When control resources are limited, the reflective system is restricted leading to weaker "restraint standards" (p. 163) and weaker behavioral monitoring mechanisms (Hofmann et al., 2009), which paves the way for the impulsive system (Hofmann et al., 2009).

1.2. The theory of self-regulation

Self-regulation implies exercising control over oneself and "consists of deliberate efforts by the self to alter its own states and responses, including behavior, thoughts, impulses or appetites, emotions, and task performance" (Baumeister, 2007, p. 841). Such changes in the own self happen through self-regulation mechanisms, which according to Bandura (1991) consist of self-monitoring, judgmental, and self-reactive functions. Self-regulation is not identical with the reflective system but can rather be understood as a resource that governs or fuels the reflective system (Vohs, 2006). According to Vohs (2006), self-regulation supplies the resources, which can be used in situations in which individuals attempt to control themselves. In a similar vein, Sherman et al. (2008) argue that self-regulation is crucial in situations that are characterized by a competition between automatic impulsive associations and reflective processes. Although dual-process models often do not explicitly refer to self-regulation, they are highly intertwined with self-regulation, as they are concerned with determining under which circumstances individuals' judgment and behavior are driven by automatic, impulsive processes or intended controlled processes and how these compete with each other (Sherman et al., 2008). In particular, the capacity of delaying rewards and gratifications is of special relevance in the context of the RIM. This capacity to delay rewards is explained as whether or not individuals manage to overcome immediate impulses that lead to short-term gratifications and engage in the achievement of long-term goals instead (Baumeister, 2007). In line with the logic of the RIM, this behavior implies the activation of self-regulation resources as well as the reflective system (Hofmann et al., 2009).

In the context of reflective smartphone disengagement, self-regulation is a relevant concept because low levels of self-regulation may lead to addictive behavior (Baumeister, 2007), whereas high levels can result in reflective processes (Vohs, 2006). In fact, previous research found that lower levels of self-regulation increase the risks of addictive smartphone behavior (Van Deursen, Bolle, Hegner, & Kommers, 2015). Whether individuals can resist stimuli emerging from their smartphone utilities highly depends on the goal they want to achieve as well as on their capabilities to overcome the impulse to engage with the smartphone (see Berger, Wyss, & Knoch, 2018). Based on the logic of the self being "an active agent that measures, decides, and intervenes in its own processes to change them" (Baumeister, 2007, p. 842), we argue that besides the impulsive temptations of smartphones, individuals possess the capability to reflectively disengage from their smartphones.

Previous research extensively focused on the influences of the impulsive system (according to the RIM logic) in connection with mobile phone/smartphone behavior. The findings highlight that impulses which are not controlled by the reflective system are likely leading to excessive smartphone use behavior, like checking the phone regularly (e.g., Wilmer & Chein, 2016), limiting individuals to cope with their lives (e.g., Turel & Qahri-Saremi, 2016). These excessive forms are typically "conceptualized as a behavioral addiction including the core components of addictive behaviors" (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015, p. 157). Research on the single components of impulsivity further showed that there is, for instance, a positive relationship between lack of perseverance and excessive smartphone use (Contractor, Weiss, Tull, & Elhai, 2017).

Even though the logic of the RIM suggests that behavior is influenced by an interaction between the impulsive and the reflective system (Schnauber-Stockmann et al., 2018; Strack & Deutsch, 2004), previous research largely focused on the impulsivity of smartphone use. By contrast, we aim to broaden the understanding of how the reflective system functions in terms of reflectively disengaging from smartphones by proposing a new concept.

2. Importance of the reflective smartphone disengagement concept

It is important to note that the reflective use of the smartphone is not the simple opposite of impulsive use (e.g., see Vanden Abeele, 2020), most often conceptualized as excessive use. We, therefore, cannot use the inverse of measures tapping impulsive use to track the reflective use of the smartphone. More specifically, the opposite of excessive use is non-use or very infrequent use. Yet non-use or infrequent use does not necessarily have to be reflective, people may not use their smartphone for other reasons as well (i.e., without much reflection). Scholars have primarily been interested in excessive use, and the stressful consequences that come with it. However, it is also relevant to show that smartphone use can be deliberatively controlled.

In a given situation, certain cues (e.g., a disruption by the smartphone) can prompt individuals to consider how and if they want to use their smartphone. This reflective process can then lead to disengagement, as for instance, putting the phone away, not checking it, or not responding to it. Such reflection only occurs under the condition that there are available cognitive resources. When these reflective episodes repeatedly occur over time, that is, repeatedly lead to a reflective disengagement, then individuals develop conscious deliberative usage rules for specific situations. More specifically, conscious deliberative usage rules are understood as a *motivation to regulate smartphone use in a specific situation*. For instance, individuals may be motivated not to use their smartphone in certain contexts (e.g., at dinner), or at certain places. Russo et al. (2019) demonstrated that decisions to disengage from smartphones occur on two levels: logic of appropriateness and logic of consequence. Motivations that drive individuals' disconnection include: "improving role performance, establishing personal digital philosophy, minimizing undesirable social behaviors, and shielding one's priorities in life" (Russo et al., 2019, p. 14). Over time, such deliberative rules can be applied in several situations, and therefore, we can measure RSD as a stable disposition. To be clear, RSD can be both, state-like and trait-like. That is, disengagement can shift throughout the day, depending on the characteristics of the situation, needs from the social or work environment, or the available cognitive resources. Across situations, however, we theorize that individuals develop generalized rules for specific situations. In this paper, we are primarily interested in such trait-like RSD.

Taken together, *RSD means that people deliberatively develop rules for when and how it is appropriate to use the smartphone,* and such rules are theorized to be stable over time. We use the word "reflective" because individuals have invested cognitive efforts to consciously determine those rules. We speak of disengagement because individuals will be motivated to restrict their smartphone use in such situations. Again, it is important to note that RSD is not the same as non-use. Non-use would be to generally restrict smartphone use. RSD, by contrast, means that individuals only restrict their use in specific situations. Apart from such situations, they may regularly or heavily use their smartphones.

We argue that both notions, reflective and impulsive, are theoretically distinct; they should be distinguishable in empirical research and relate to different antecedents and outcomes. However, existing scales on addictive use have ignored the reflective side. For instance, the Smartphone Addiction Proneness Scale (Kim, Lee, Lee, Nam, & Chung, 2014) distinguishes four dimensions, namely the disturbance of adaptive functions (e.g., "People frequently comment on my excessive smartphone use"), virtual life orientation (e.g., "Using a smartphone is more enjoyable than spending time with family or friends"), withdrawal (e.g., "I get restless and nervous when I am without a smartphone") and tolerance (e.g., "Spending a lot of time on my smartphone has become a habit"). As should be apparent, none of these dimensions addresses the deliberate effort to control smartphone use. The same is true for other prominent concepts, such as Internet Addiction (Young, 1996), Compulsive Internet Use (Meerkerk, Van Den Eijnden, Vermulst, & Garretsen, 2009; seven dimensions: tolerance, withdrawal symptoms, loss of control, preoccupation, conflict, coping, lying about involvement), or Generalized Problematic Internet Use (Caplan, 2010; five dimensions: preference for online social interaction, mood regulation, cognitive preoccupation, compulsive use, negative outcomes).

It is important to note that there are some related but conceptually different constructs. For instance, metacognition refers to the management and understanding of one's thinking processes (Wilmer & Chein, 2016). The construct consciousness refers to the subjective experience of oneself and one's environment, i.e., the awareness of one's feelings and emotions and the awareness of, and perceived control over, one's thoughts and behaviors. Conscious mobile phone use (Bayer et al., 2016) is measured with aspects such as immersion, presence, or absorption. Habitual Smartphone Behavior (Limayem, Hirt, & Cheung, 2003) is defined as automatic behavior triggered by situational cues (ringtone) or internal cues (urgency). Finally, self-control as a personality trait is the ability to control one's thoughts, emotions, urges, and behaviors (Bayer et al., 2016). Taken together, the literature suggests that there is a clear need to develop and validate a new concept tapping RSD.

We conducted four independent studies to show a full validation of our RSD concept. In Study 1, we conducted an exploratory factor analysis of a newly developed RSD scale. In Study 2, we conducted a confirmatory factor analysis, test-retest reliability analysis and tested construct validity, specifically discriminant and predictive validity. In Study 3, we looked at convergent validity by correlating RSD with two theoretically important personality traits. Study 4 was an additional validation using confirmatory factor analysis.

3. Study 1

The first step was to create a RSD measure. We theorized that RSD is a one-dimensional construct that can be measured in reliable ways. To test the construct, we performed principal axis factor analysis (PAF) as well as confirmatory factor analysis (CFA).

3.1. Method

Item construction. Based on the theoretical conceptualization of RSD, we designed a new scale. As detailed above, we theorize that individuals deliberately develop generalized rules for when and how to use the smartphone. These rules are understood as a motivation to regulate smartphone use in specific contexts. In line with this definition, we developed the following six items: (1) "There are certain periods during the day (e.g., while eating) when I do not want to use my mobile phone" (2) "There are certain places (e.g., in the bedroom, on the toilet); where I do not want to use the mobile phone" (3) "There are certain situations (e.g., on holiday, in presence of friends); in which I do not want to use the mobile phone"; (4) "I pay attention that my cell phone does not play a role in my life that is too big"; (5) "It is important to me that I decide when I can be reached, and not that my mobile phone determines it"; (6) "There are situations in which I do not want to be reachable, which is why I switch off the mobile phone, consciously put it away, or don't look at it". We assessed the six RSD items, ranging from (1) "completely disagree" to (5) "completely agree" (M = 2.54, SD = 0.89, α = 0.74). We treat RSD as a reflexive measure, because we expect items to be correlated due to a shared variance. Also, the items do not refer to single situations, but to the fact that RSD situations occur in principle. Online Appendix displays the original items in German. We used a translation-back-translation procedure to validate the translations reported here. Data of all studies are available at OSF (https://osf.io/6y238/?view_only=b2004b81da46477f816ff9f250546787).

Sample and procedure. We conducted a cross-sectional survey among adolescents in Austria. The online questionnaire was disseminated among pupils in three high schools in one large city. Pupils filled out the online questionnaire as part of course workshops within a larger project on media literacy. They were informed about the purpose of the survey and their anonymity was assured. A total of 453 pupils aged

14–21 years took part in the online questionnaire. The sample consisted of 57.6% girls (M_{age} = 15.70 years, SD = 1.26) and 91.2% of the participants owned a smartphone device.

3.2. Results

The size of the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = 0.802) and Barlett's test of sphericity, χ^2 = 453,87, $p < .001$, suggested that the data was factorable. The Shapiro-Wilk tests ($p < .001$) revealed that the normality assumption for all items of interest was violated. To account for this violation of the normality assumption, we used principal axis factoring (PAF) assuming non-independent factors for the factor analysis. The analysis yielded a one factor-solution, which explained 43.91% of the variance. The scale was reliable, α = 0.74. As can be seen in Table 1, all factor loadings are higher than 0.4. To maintain the breadth of the construct, we decided not to exclude items at this stage.

We also conducted a confirmatory factor analysis (CFA) with the *lavaan* package in R (Rosseel, 2012). We do this because CFA can serve as a cross-validation for PAF, as long as the CFA findings are validated with independent samples (Gerbing & Hamilton, 1996). To deal with missing data we used the full-information maximum likelihood method (FIML) and robust maximum likelihood estimator to account for the violation of the normality assumption. We estimated the model fit by determining the chi-square, the degrees-of-freedom ratio (χ^2/df), the comparative fit index (CFI), the Tucker–Lewis index (TLI) and the root mean square error of approximation (RMSEA; Schreiber, Nora, Stage, Barlow, & King, 2006). We reported the robust CFI, TLI and RMSEA. The results revealed an acceptable model fit: $\chi 2$ (9) = 27.48, χ/df = 3.05, $p <$ .001; CFI = 0.953; TLI = 0.922; RMSEA = 0.075, 90% CIs [0.044; 0.108], with all six items showing significant and high estimates (see Table 2).

3.3. Discussion

The first study provides initial evidence for the dimensionality, reliability, and structural validity of the construct. However, the scale needs to be applied to independent samples. Most importantly, findings from the present study cannot be generalized to adult samples. Finally, while Study 1 was able to demonstrate basic facets of validity, a more comprehensive validity test is necessary. In Study 2, a full construct validation process (John & Benet-Martinez, 2000) will be presented. We outline the examination of predictive and discriminant validity and we examine test-retest reliability using panel data.

Table 1
Factor loadings based on the principal axis factoring.

Reflective Smartphone Disengagement Scale Items	Study 1: Adolescent sample Item-factor loadings
Item1. There are certain periods during the day (e.g., while eating) when I do not want to use my mobile phone.	.538
Item2. There are certain places (e.g., in the bedroom, on the toilet) where I do not want to use the mobile phone.	.503
Item3. There are certain situations (e.g., on holiday, in presence of friends) in which I do not want to use the mobile phone.	.693
Item4. I pay attention that my cell phone does not play a role in my life that is too big.	.670
Item5. It is important to me that I decide when I am to be reached and not that my mobile phone determines it.	.554
Item6. There are situations in which I do not want to be reachable, which is why I switch off the mobile phone, intentionally put it away or do not look at it.	.460

4. Study 2

Predictive validity can be defined as the ability of a scale to predict a criterion based on theoretical arguments (John & Benet-Martinez, 2000). In the following section, we lay out four criteria: excessive use, information overload, privacy concerns, and social availability norm. All four can be defined as outcomes of RSD. In addition to predictive validity, we test the discriminant validity of the RSD scale by relating it to the concept of excessive smartphone use (Lin et al., 2015). If RSD is a unique concept tapping the reflective system, then it should be empirically distinct from excessive use, which—partially—reflects the impulsive system. Impulsivity has been recognized as one of the underlying pathways to excessive or addictive use (Billieux et al., 2015). Finally, we also examine test-retest reliability. The reason for this step is that RSD, similar to excessive use, can be understood as a trait-like concept. That is, individuals' deliberate efforts to control and restrict their smartphone use should be rather stable over time. Hence, individuals develop generalized patterns of restricting their smartphone use across specific situations.

4.1. Excessive use

Even though smartphones offer far more opportunities and activities than the classic mobile phones (Billieux, 2012), the focus of attention has shifted to the possible negative consequences associated with an uncontrolled and/or excessive use of smartphones (see Billieux, 2012; Lin et al., 2015). The excessive usage potential of mobile phones, in general, derives form the opportunity they provide to the users to flee from difficult situations (Bianchi & Phillips, 2005) while "providing comfort" (Diefenbach & Borrmann, 2019, p. 1). However, it is important to note that excessive mobile phone use cannot be defined as mere function of escaping difficult situations and providing comfort. Instead, excessive use encompasses multiple utilities and antecedents (Billieux et al., 2015). Excessive mobile phone use, can take many forms, such as enormously focusing on the phone, increasingly spending time on the phone to meet the rising expectations to feel satisfied with one's own use, or feeling restless when attempting to reduce usage (Lee et al., 2014). More importantly, based on the logic of the RIM, uncontrolled urges and deregulated use of the smartphone can be driven by specific impulsivity traits, such as low self-control (e.g., Billieux et al., 2015; Van Deursen et al., 2015). Our focus, however, lies on the reflective system of the RIM as well as on self-control mechanisms, which leads to the following hypothesis:

H1. Reflectively disengaging from the smartphone negatively predicts excessive smartphone use over time.

4.2. Information overload

Smartphones offer users a nearly unlimited access to mobile Internet, SNSs, mobile applications, as well as all sorts of information (Lee, Son, & Kim, 2016). This immense access leads to a *Permanently Online and Permanently Connected* (POPC) mindset as defined by Vorderer, Hefner, Reinecke, and Klimmt (2018). One consequence of being constantly online and connected is that the separation between real-world communication and online engagement becomes indistinct, even overlapping, with the smartphone being the unifying element (Vorderer et al., 2018). The POPC mindset implies that smartphone users are not only exposed to information about their offline environment but also get constantly exposed to information online, which might result in perceived information overload (LaRose, Connolly, Lee, Li, & Hales, 2014).

Information overload is defined as "receiving too much information", which makes individuals feel incapable of processing the abundance of available, incoming information (Eppler & Mengis, 2004, p. 326). Previous research addressed information overload in connection

Table 2
Confirmatory Factor Analysis using Full Information Maximum Likelihood with the Robust Maximum Likelihood Estimator for all studies.

	Study 1		Study 2		Study 3		Study 4	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE
RSD (T1)								
Item1_T1	1.00+		1.00+		1.00+		1.00+	
Item2_T1	1.05***	0.13	1.10***	0.07				
Item3_T1	1.29***	0.14	1.01***	0.06	1.14***	0.09	1.03***	0.10
Item4_T1	1.08***	0.12	1.03***	0.06	0.93***	0.07	1.06***	0.11
Item5_T1	0.83***	0.12	0.88***	0.05	1.04***	0.11	1.06***	0.13
Item6_T1	0.80***	0.13	0.98***	0.05	1.11***	0.10	1.17***	0.14
RSD (T2)								
Item1_T2			1.00+					
Item2_T2			1.01***	0.08				
Item3_T2			1.03***	0.07				
Item4_T2			0.91***	0.06				
Item5_T2			0.86***	0.06				
Item6_T2			1.02***	0.06				
Fit Indices								
$\chi^2(df)$	27.48 (9)		162.32 (4)		44.19 (5)		20.625 (5)	
Robust CFI	0.953		0.948		0.946		0.957	
Robust TLI	0.922		0.927		0.892		0.913	
Robust RMSEA	0.075		0.068		0.110		0.083	

with social networking sites (SNS) (e.g., LaRose et al., 2014; Lee et al., 2014), email communication (e.g., Barley, Meyerson, & Grodal, 2011) or online news exposure (e.g., Schmitt, Debbelt, & Schneider, 2018). In the context of the POPC mindset, research addressed the role of impulsive and reflective behavior. Smartphones offer the possibility to immediately react to impulses, like checking for information, which may further increase the risks for compulsive behavior (Hefner, Knop, & Klimmt, 2018). Nonetheless, the reflective system plays an important role because it helps individuals to distance themselves from this constant connectivity through self-control mechanisms (Hefner et al., 2018; Van Koningsbruggen, Hartmann, & Du, 2018). Based on the rationale that the smartphone is a key element when experiencing an overwhelmingly amount of information from both the offline and online environment, we formulate the following hypothesis:

H2. Reflectively disengaging from the smartphone negatively predicts information overload over time.

4.3. Privacy concerns

Research showed that based on a trade-off between risks and benefits, users are ready to disclose private information in the context of SNSs as well as on smartphone applications (Dienlin & Metzger, 2016; Wang, Duong, & Chen, 2016). Concerns about the protection of personal information and one's privacy are on the rise since many smartphone applications require personal user information for their services. Some smartphone applications even go one step further and require personal information to offer personalized services, which is referred to as the "personalization-privacy paradox" (Sutanto, Palme, Tan, & Phang, 2013, p. 1142). Smartphone users feel more worried about their privacy when they use a smartphone compared to a laptop and act more carefully, when doing activities that touch personal information, e.g., revealing financial or health details (Chin, Felt, Sekar, & Wagner, 2012).

Accordingly, one could argue that the more people restrict their smartphone use, the less they need to be concerned about privacy issues. In other words, when there is no smartphone use, there is arguably also no reason to be concerned about one's privacy. The reason behind this relationship lies in the feeling of perceived control. Engaging in reflective reasoning and thus deliberatively choosing to restrict smartphone use increases perceived control about the smartphone and the consequences of its use. Such perceived control should then lead to fewer perceptions of privacy concerns. Although it is impossible at this stage to derive assumptions about causal order, one could thus theorize that RSD may limit privacy concerns. Thus:

H3. Reflectively disengaging from the smartphone negatively predicts privacy concerns over time.

4.4. Social availability norm

Constant access to mobile Internet, mobile SNS, or applications offering instant messaging services (e.g., Facebook, WhatsApp, Instagram) facilitates social interaction online and increases feelings of being connected. These services, however, can also lead to negative experiences on the users' side, like feeling strong social norms to instantly react to incoming information and communication (Knop et al., 2015). In light of the numerous services offered by smartphones, users learned to respond quickly or even instantly to incoming information. Functions providing the sender of a message with the information when the message was read by the receiver, such as the seen-function on the SNS Facebook, increase the perceived obligation to react instantly (Mai, Freudenthaler, Schneider, & Vorderer, 2015). Similar findings were shown in the context of answering to emails as fast as possible, leading to stress (Barley et al., 2011).

The concept of a social availability norm stands for mobile phone behavior that is based on the individual's internalized norms regarding the close social circle (Hall, Baym, & Miltner, 2014). The perception of group behaviors in terms of social availability through smartphones can have a significant influence on people. Specifically, people can easily adopt the constant use of smartphones and deem this behavior as socially acceptable. In fact, peer availability norms were found to be influential among children and adolescents (Knop et al., 2015). The readiness of children and adolescents to behave according to the influence of their peers was found to be connected to higher levels of involvement with their smartphones (Knop et al., 2015). Research also highlighted that the need to belong to a group and the fear to be socially excluded related to obligations to answer immediately and to expect others to answer immediately (Mai et al., 2015, p. 300). These findings can be interpreted within the realm of Kelman's (1958, p. 53) social influence theory, which describes different stages of social influence on individuals' attitudes and behaviors, namely: *compliance* (i.e., the acceptance of influence for positive reactions from a person or a group), *identification* (i.e., the acceptance of influence leading to the adoption of behavior or assimilation of opinions for positive relationships with a person or a group), and *internalization* (i.e., the acceptance of influence because it is "intrinsically rewarding" and in line with opinions or behaviors of a person or a group) (see also Wang, Meister, & Gray, 2013, p. 300). Based on this theory, it can be argued that the social availability norm led to an internalization of automatically engaging with the smartphone. Reflectively disengaging from the smartphone, however, would imply that smartphone users manage to distance themselves from the social availability norm of their social environment. We propose the following hypothesis:

H4. Reflectively disengaging from the smartphone negatively predicts the social availability norm over time.

4.5. Method

Sample and procedure. A private polling company conducted a two-wave panel survey among late adolescents and adults in Germany. The first wave took place in March and April 2018 and the second wave in July and August 2018. The time interval between the two waves was four months based on feasibility considerations and previous research (Yao & Zhong, 2014). We informed the participants about the purpose of the study, the content of the questionnaire, and ensured anonymity. Only participants who gave their consent were included. The requirements to participate were (1) the possession of a smartphone, and (2) use of at least one SNS on their smartphone before participation. We used a quota sample with regard to gender, age, and education.

A total of 833 participants, aged between 16 and 65 years, took part in the study at Time 1 (54.1% women; $M_{age} = 45.44$ years, $SD = 14.83$). A total of $N = 461$ took part in the study at Time 2 (53% women; $M_{age} = 48.65$ years, $SD = 13.02$; attrition rate: 45%). Participants who did not take part in the second wave slightly differed regarding their reflective smartphone disengagement F (1,808) = 8.65, $p = .003$, $\eta^2 = 0.01$, excessive use F (1,814) = 4.34, $p = .038$, $\eta^2 = 0.01$, information overload F (1,831) = 10.74, $p = .001$, $\eta^2 = 0.013$, and social availability norm F (1,825) = 6.27, $p = .013$, $\eta^2 = 0.01$. Yet effect sizes are small ($\eta^2 < 0.06$) (see Cohen, 2013).

Measures. The online Appendix displays all items, assessed on a 5-point scale from (1) "completely disagree" to (5) "completely agree". To assess *RSD* we used the same six items as in Study 1 (Table 1, $M = 3.99$, $SD = 0.79$, $\alpha = 0.85$ at Time 1; $M = 4.01$, $SD = 0.77$, $\alpha = 0.86$ at Time 2). We measured *excessive use* with three items from the smartphone involvement scale (Clark, Algoe, & Green, 2018; e.g., "Even when I am busy with something else, I often look at my mobile phone or check messages") and four items from the deficient Internet self-regulation scale (Deters & Mehl, 2013) (adapted to the context of smartphones). As will be explained below, we had to exclude two items in the full structural equation model involving all constructs at Time 1 and Time 2, to obtain an acceptable model fit. We computed an one-dimensional index of five items, which we used in the final analysis ($M = 2.48$, $SD = 1.00$, $\alpha = 0.88$ at Time 1; $M = 2.34$, $SD = 1.00$, $\alpha = 0.89$ at Time 2). To gauge *information overload* we asked the participants to indicate their agreement on three items, adapted from Karr-Wisniewski and Lu (2010) to fit them to the topic of our study (i.e., mobile phone use) (e.g., "I find that I am overwhelmed by the amount of information I have to process on my mobile phone on a daily basis"; $M = 2.43$, $SD = 1.03$, $\alpha = 0.87$ at Time 1; $M = 2.24$, $SD = 1.02$, $\alpha = 0.85$ at Time 2). We measured *privacy concerns* using the scale adapted from Hsu and Lin (2018; see Mani & Chouk, 2017; e.g., "I worry about my privacy when I use social media platforms on the phone"; $M = 3.69$; $SD = 0.96$; $\alpha = 0.89$ at Time 1; $M = 3.55$; $SD = 1.04$; $\alpha = 0.90$ at Time 2). Lastly, we measured *social availability norm* with four items based on the scale by Hall et al. (2014) adapted from Knop et al. (2015; e.g., "In my circle of friends, it is normal that one answers immediately to messages, e.g., SMS, WhatsApp"; $M = 2.74$, $SD = 0.94$, $\alpha = 0.79$ at Time 1; $M = 2.58$, $SD = 0.98$, $\alpha = 0.82$ at Time 2). As covariates we included age, gender, and educational level, i.e., lower than high school degree (67.2%) and high school degree or higher (32.8%).

4.6. Data analysis

We used Structural Equation Modeling with a Full Maximum Likelihood estimate because of missing values. We assessed the chi-squared to degrees of freedom ratio (χ^2/df), the Comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) to calculate the model fit. Criteria for good model fit are RMSEA values lower than 0.06 and a CFI or TLI higher than 0.95 (Schreiber et al., 2006). Also, the criteria for an acceptable model fit are RMSEA values between 0.05 and 0.08 as well as CFI or TLI values between 0.90 and 0.95 (Byrne, 2001). We controlled for *autoregressive effects* and error terms of the same items were allowed to correlate over time.

4.7. Results

In a first step, to test structural validity, we performed confirmatory factor analysis (CFA) including all six items from the reflective smartphone disengagement scale at Time 1 and at Time 2. We conducted our analyses in the package *lavaan* in R (Rosseel, 2012). To test whether our items followed a normality distribution we used the Shapiro-Wilk test, which revealed that the normality assumption for all items of interest was violated ($p < .001$). To account for this violation of the normality assumption, we used the robust maximum likelihood estimator and report the robust CFI, TLI and RMSEA. The results revealed an acceptable model fit: $\chi 2$ (47) = 162.32, $\chi/df = 3.45$, $p < .001$; CFI = 0.948; TLI = 0.927; RMSEA = 0.068, 90% CIs [0.057; 0.080], with all six items showing significant and high estimates (see Table 2).

We then turned to the full autoregressive SEM model, as depicted in Fig. 1. The results are shown in Table 3. The initial results including the seven excessive use items did not indicate acceptable model fit χ^2 (781), 1871.039, $p < .001$; CFI = 0.913; RMSEA = 0.055, 90% CIs [0.052; 0.058], $p = .005$). Excluding two items increased the model fit: χ^2/df (625), 2.187, $p < .001$; CFI = 0.932; RMSEA = 0.051, 90% CIs [0.047; 0.054], $p = .355$. All hypothesis tests did not differ between the two models.

In our first hypothesis, we expected that RSD would decrease excessive use over time. Our results showed that RSD at Time 1 negatively predicted excessive use at Time 2 while controlling for excessive

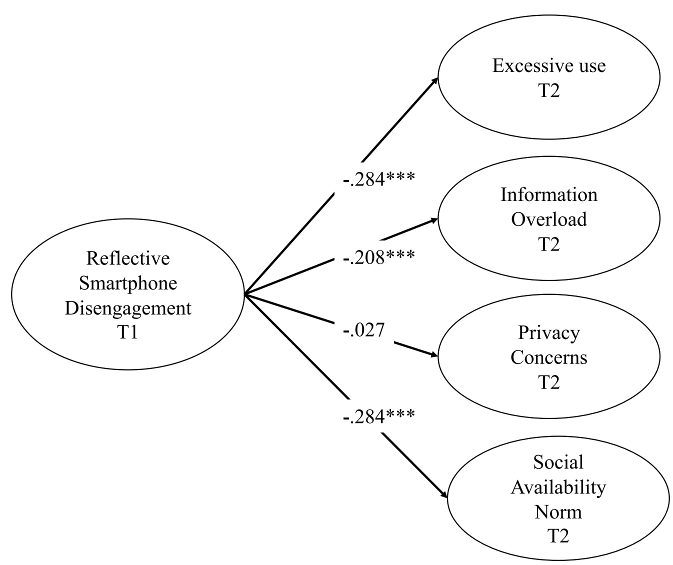

Fig. 1. The results of the hypothesized model analyzed in SEM showed acceptable model fit: χ^2/df (625), 2.187, $p < .001$; CFI = 0.932; RMSEA = 0.051, 90% CIs [0.047; 0.054], $p = .355$. Ovals present latent variables. We controlled for auto-regressive effects of each dependent variable, age, gender, and education. For clarity reasons, error terms, covariances, controls, and measurement items are not shown. T1 = Time 1; T2 = Time 2. *$p < .05$; **$p < .01$; ***$p < .001$. $N = 461$ participants from Study 2 who completed the survey at both the T1 and the T2 assessments.

Table 3
Results of the hypothesized structural equation model.

	Excessive Use (T2)		Information Overload (T2)		Privacy Concerns (T2)		Social Availability Norm (T2)	
	b	SE	b	SE	b	SE	b	SE
Predictor								
Age (T1)	-.061*	.030	-.050	.035	-.010	.027	-.045	.026
Gender (T1)	-.014	.071	-.044	.084	-.016	.064	.026	.061
Education (T1)	.098	.073	.002	.087	.128	.066	-.095	.063
RSD (T1)	-.284***	.072	-.208*	.084	-.027	.063	-.284***	.064
Excessive Use (T1)	.801***	.167						
Information Overload (T1)			.316**	.136				
Privacy Concerns (T1)					.625***	.054		
Social Availability Norm (T1)							.741***	.136
R^2	.66		.39		.43		.60	

Note. $N = 461$, T1 = Time 1, T2 = Time 2, RSD = Reflective Smartphone Disengagement, $^*p <. 05$, $^{**}p <. 01$, $^{***}p <. 001$.

use at Time 1 ($b = 0.284$, $SE= 0.072$, $p < .001$). Hence, H1 was confirmed. In our second hypothesis, we assumed that RSD would decrease information overload over time. Findings indicated that reflective smartphone use at Time 1 negatively predicted information overload at Time 2 while controlling for information overload at Time 1 ($b = -0.208$, $SE = 0.084$, $p = .014$). Therefore, H2 was also supported.

In contrast to our third hypothesis, we found no influence of reflective smartphone disengagement at Time 1 on privacy concerns at Time 2 while controlling for privacy concerns at Time 1 ($b = -0.027$, $SE = 0.063$, $p = .668$). Thus, we could not support H3. In line with our fourth hypothesis, reflective smartphone use at Time 1 negatively predicted social availability norm at Time 2 while controlling for social availability norm at Time 1 ($b = -0.284$, $SE = 0.064$, $p < .001$). Thus, H4 was supported (see Table 3).

Test-retest reliability. In order to calculate test-retest reliability, we modeled RSD as a latent variable at Time 1 and Time 2. Since we are interested in the relationship between both points in time, we need to establish metric invariance for the construct, that is, equal factor loadings over time (Kline, 1998). We conducted a nested model comparison, where we compared a model without constraints with a model assuming loadings of the same items to be equal. This comparison did not lead to a worse model fit ($p = .434$). Therefore, we can assume metric invariance, and based on that, estimate the correlation between the two latent variables. The correlation was highly significant, $r = 0.737$, $p < .001$, and the model fit was acceptable: CFI = 0.945, TLI = 0.936, RMSEA = 0.076, 90% CIs [0.065; 0.087].

Discriminant validity. We tested discriminant validity by nested model comparison (Kline, 1998). We compared a two-factor model, consisting of RSD and excessive use with a one-factor model in which all items loaded on one dimension. The one-factor model yielded a significantly worse model fit ($p < .001$), suggesting that RSD and excessive use are two distinct constructs. Both constructs are only moderately correlated, $r = 0.423$.

4.8. Discussion

Findings from Study 2 replicated those from Study 1. RSD is a one-dimensional construct that can be measured in reliable ways. We also demonstrated the predictive validity of the scale by relating it to excessive use, information overload, and the social availability norm. It is important to note that we conducted an autoregressive SEM, which can be considered a conservative test of all the relationships. Thus, RSD predicts theoretically related constructs over time. We also found high test-retest reliability suggesting that the patterns of disengagement remain rather stable over time. This result is comprehensible, because deliberative rules to use the smartphone, by definition, should be applied across situations.

Finally, our data showed that RSD and excessive smartphone use are distinct but correlated constructs. The correlation, however, is not perfect (i.e., 1), which can be explained in two ways. First, our findings suggests that not all individuals with excessive use behavior are also completely avoiding RSD. This suggests a person may face situations with excessive use, and then disengage in other situations. It may also be the case that individuals reach some very high levels of excessive use, and react with RSD as a response to regain control. Second, as explained above, certain impulsive traits can predict excessive use. However, conceptually, excessive use cannot be equated with impulsivity – and therefore, it is not entirely indicative of the impulse system as opposed to the reflective system as proposed in the RIM. This could be the reason for the relationship. We nonetheless conclude that, overall, the empirical data from this study corroborates our claim for the need of the RSD concept. However, as another facet of construct validity, we need to test convergent validity.

5. Study 3

We use two personality traits to test convergent validity. Here, we do not make assumptions about a criterion we predict, because RSD is also a trait-like construct making it difficult to derive assumptions about causal order. We thus access correlations. We choose two constructs, the traits nomophobia and self-reflection.

5.1. Nomophobia

In the POPC mindset, the smartphone has become an essential device for keeping the ties with friends and family, remaining up to date about the latest events, or receiving help or information in difficult situations (see Lee et al., 2016). As a result, a phenomenon called nomophobia is increasingly prevalent among smartphone users. Nomophobia has been described as a phobic trait (e.g., Tams, Legoux, & Léger, 2018) that manifests itself in a state of anxiety when being without one's phone (King et al., 2013; Yildirim & Correia, 2015). As other phobias, nomophobia is a situational phobia that is related to various symptoms, when individuals find themselves in a situation, in which they are not able to use their smartphones (King et al., 2014). Studies on nomophobia showed that when heavy and moderate smartphone users were separated from their devices, they felt more anxious (Cheever, Rosen, Carrier, & Chavez, 2014). It was also found that nomophobia, on the one hand, led to stress among users when they felt insecure or a lack of control about the situation (Tams et al., 2018). On the other hand, when users knew how long they were separated from their phones and had control over the situation, it did not lead to stress anymore (Tams et al., 2018). We extrapolate these findings to the rationale of RSD. We argue that nomophobia might be negatively related to RSD for two reasons. First, people with high levels of nomophobia may perceive the smartphone as an important source of security and may therefore be less likely to engage in RSD. Second, RSD implies higher levels of control, which might decrease fear of being without the smartphone, i.e. nomophobia. Therefore we propose:

H5. There is a negative relationship between trait nomophobia and reflective disengagement from one's smartphone.

5.2. Self-reflection

Based on the RIM (Strack & Deutsch, 2004), we included the trait self-reflection as an important concept for establishing a relationship with our scale. Self-reflection is among other aspects connected to investigating and assessing an individual's own thoughts, feelings, and behavior (Carver & Scheier, 1998; Grant, Franklin, & Langford, 2002). In the context of smartphone use, self-reflection is of great relevance. If smartphone users do not reflect on their behavior when the phone offers a tempting stimulus, it would mean that the impulsive system has an advantage compared to the reflective system and thus drives behavior (see RIM; Hofmann et al., 2009; Strack & Deutsch, 2004). Previous research found that there is a negative relationship between conscientiousness and phone use, meaning that less conscientious individuals are more engaging with their phones via texting (Butt & Phillips, 2008). Thus, increased capabilities to self-reflect on one's action should also make people more likely to engage in RSD. Therefore, we propose the following hypothesis:

H6. There is a positive relationship between self-reflection and reflective disengagement from one's smartphone.

5.3. Method

Sample and procedure. We conducted a cross-sectional study among late adolescents in Germany through a private research institute in August 2019, $N = 760$. Participants confirmed their consent before survey participation. They were informed about the content of the questionnaire and the study goals. We assured their anonymity. Only active smartphone users aged between 16 and 19 years took part in the questionnaire (78.6% girls; $M_{age} = 17.65$, $SD = 1.04$; 45% attended high school).

Measures. We used a 5-point scale from (1) "completely disagree" to (5) "completely agree" (see Online Appendix). The same six RSD items were used (Table 1, $M = 3.52$, $SD = 0.84$, $\alpha = 0.76$). We measured *nomophobia* with the scale form Yildrim and Correia (2015; e.g., "I would feel anxious because I could not instantly communicate with my family and/or friends"; $M = 2.61$, $SD = 0.98$, $\alpha = 0.81$) and trait *self-reflection* with an adapted Self-Reflection and Insight Scale, e.g., "I often reflect on how I am feeling" (Grant et al., 2002; Yang & Bradford Brown, 2016; $M = 3.59$, $SD = 0.88$, $\alpha = 0.71$).

5.4. Results

As previously, we conducted confirmatory factor analysis (CFA) of the six items from the reflective smartphone disengagement scale. The results showed unsatisfactory model fit: $\chi 2$ (9) = 103.72, $\chi 2/df = 11.52$, $p < .001$; CFI = 0.899; TLI = 0.832; RMSEA = 0.110, 90% CIs [0.08; 0.14], with five items showing estimates above 0.90 and one item showing estimate $b = 0.802$. Thus, we released this item and ran the CFA with five items. The results revealed slightly better model fit: $\chi 2$ (5) = 44.19, $\chi 2/df = 8.83$, $p < .001$; CFI = 0.946; TLI = 0.892; RMSEA = 0.123, 90% CIs [0.10; 0.14] with all five items showing high estimates as reported in Table 2.

Because of the low model fit, we conducted the EFA analysis and performed a correlational analysis with the observed variables. The data was factorable based on the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = 0.782) and Barlett's test of sphericity, $\chi 2 = 855.02$, $p < .001$. The Shapiro-Wilk tests ($p < .001$) showed none of the items were normally distributed. Therefore, we used principal axis factoring (PAF) for the factor analysis. The analysis yielded a one-factor solution, explaining 39.33% of the variance. The reliability test of the five items showed high Cronbach's Alpha = .76.

Next, we computed two-tailed Pearson's correlations to test if nomophobia and self-reflection are significantly related to reflective smartphone disengagement. We found a significant negative correlation between reflective smartphone disengagement and nomophobia ($r = -0.19$, $p < .001$), which confirmed H5. Furthermore, we found a significant positive correlation between reflective smartphone disengagement and self-reflection ($r = 0.23$, $p < .001$), which supported H6 (see Table 4).

5.5. Discussion

Study 3 provided evidence for convergent validity using a sample of adolescents. As expected, we observed a negative correlation of RSD with nomophobia and a positive one with self-reflection. The correlations are significant but of small size. The findings suggest that more disengagement from smartphones relates to less fear about being without a smartphone and more self-reflection, which is in line with the RIM (Strack & Deutsch, 2004) and self-regulation theory (Bandura, 1991; Baumeister, 2007). However, surprisingly, we had to release one item (i.e., item 2) in this study to reach acceptable levels of model ft. We therefore added a fourth study strictly testing the 5 item version used in study 3 as an additional validation.

6. Study 4

Based on the results of Study 3, we aimed to test the shorter version of five items with a follow-up study. Study 4 was designed as a strictly confirmatory test.

6.1. Method

Sample and procedure. We conducted a cross-sectional survey among $N = 672$ adults in Germany between December 2019 and January 2020. We recruited participants via a research seminar following a quota sampling plan. All participants consented to the participation in the study and were informed about the study goal, the confidential treatment of their data and their rights. Participants who indicated not to own a smartphone were excluded. Participants ranged between 16 and 83 years (55.4% women; $M_{age} = 31.31$, $SD = 15.24$; 72% had a high school degree).

Measures. We used the same five RSD items as in Study 3 measured on a 5-point scale from (1) "completely disagree" to (5) "completely agree" (see Table 1, $M = 3.78$, $SD = 0.84$, $\alpha = 0.71$).

Analysis. We conducted our analyses in the package *lavaan* in R (Rosseel, 2012). To test whether our items followed a normality distribution we used the Shapiro-Wilk test, which revealed that the normality assumption for all items of interest was violated ($p < .001$). To account for this violation of the normality assumption, we used the robust maximum likelihood estimator and report the robust CFI, TLI and RMSEA.

6.2. Results

We conducted a confirmatory factor analysis (CFA) of the five items. The results showed an acceptable model fit: $\chi 2$ (5) = 20.63, $\chi/df = 4.13$, $p < .001$; CFI = 0.957; TLI = 0.913; RMSEA = 0.083, 90% CIs [0.048; 0.122]. The estimates are displayed in Table 2.

Table 4
Pearson's correlations in Study 3 with the five-item reflective smartphone disengagement scale.

		M(SD)	Min	Max	1	2	3
1	Reflective Smartphone Disengagement	3.73 (0.86)	1	5	1		
2	Nomophobia	2.61 (0.98)	1	5	-.19***	1	
3	Self-reflection	3.59 (0.88)	1	5	.23***	.15***	1

Note. $N = 760$, *$p < .05$,**$p < .01$, ***$p < .001$.

6.3. Discussion

Study 4 validated the measurement model used in Study 3 with a strictly confirmatory approach. The five-item scale performed an acceptable level of fit. For optimal measurement models, the five-item version can be recommended for future research.

7. General discussion

We took a new stand by suggesting a new concept to the literature: reflective smartphone disengagement (RSD). Additionally, we developed a scale to measure RSD. Throughout four studies, we have provided clear evidence for the structural, predictive, discriminant, and convergent validity of the new RSD concept. Additional validation comes from the use of different age groups. Overall, RSD can be understood as a unidimensional concept that is theoretically and empirically distinct from impulsive forms of smartphone use and adds to the concept of digital well-being (Vanden Abeele, 2020). According to our findings, RSD and excessive smartphone use are only moderately correlated. Hence, RSD is not simply the opposite of excessive use or related concepts, such as addictive smartphone behavior. We theorize that although both concepts overlap to some extent, there are unique features of RSD. There may be smartphone users who use their smartphone excessively, yet nevertheless, set strict rules for themselves in some specific situations. As another important finding, we observed a high test-retest correlation of the RSD scale, which suggests that individuals who engage in RSD have developed stable patterns about when to use, and when not to use the smartphone in specific situations.

The RSD concept opens up entirely new questions for research. First of all, future scholarship should attempt to understand the *specific situational rules* that individuals have developed to restrict their smartphone use. That is, some may prefer not to use the smartphone during a private dinner, but have it at hand while driving a car. There may be huge interindividual variability and the myriad of situations in which individuals restrict their smartphone use are far from being fully understood. Second, and related to this, we need more evidence regarding the antecedents of RSD. Some reflective decisions may be socialized through parents and school, others may stem from negative experiences in specific situations, or from negative reactions in the social environment. That is, individuals may use the smartphone in non-reflective ways in a first step, and after a set of experiences, later deliberatively decide how and when they prefer not to use the device. This may point to individual appropriation trajectories (e.g., Russo et al., 2019).

Third, RSD may be used as an independent variable, dependent variable, and a moderator. We hope that our new RSD concept may help to resolve some of the contradictory results found in research areas such as social media use and well-being (see e.g., Orben, Dienlin, & Przybylski, 2019). As an independent variable, we assume that RSD can be used to predict the same outcomes than dimensions of excessive use such as stress or well-being (e.g., Lee et al., 2014; Thomée et al., 2011). However, to make a difference, RSD should explain outcomes above and beyond excessive use. In addition, RSD can be predicted by negative experiences, such as privacy issues or bullying experiences. The causal relationship between social media monitoring applications and RSD is another exciting new area of research. Finally, RSD may serve as a moderating variable. It may shield respondents against the negative effects of some forms of use (e.g., Wang, Gaskin, Rost, & Gentile, 2018). Especially the interaction of excessive use with RSD as well as the interaction of non-communicative smartphone use with RSD may be interesting aspects to explore. If individuals set clear rules for themselves about their uses of the smartphone, they may do so to circumvent the negative outcomes of smartphone use.

Fourth, we need of course additional studies on the measurement and validation of RSD. The scale needs to be applied to different settings, in different countries, and languages. A cross-cultural validation could path the ways for a more universal application of the scale. Especially when it comes to predictive validity, scale validation is a continuous process that does not end with one study. Most importantly, the scale should be used for first-time users or early adopters of the smartphone, preferably in research with longer time intervals.

7.1. Broader implications

Given that the smartphone increasingly becomes the main vehicle for media use, RSD is not only relevant for research on mobile communication, but also has broader implications for other areas of the field. Research on news use, for instance, may use the RSD concept to further explain information overload or news avoidance. In line with this, scholars interested in media literacy, and advertising literacy in particular, can integrate RSD to help individuals, and especially vulnerable populations, to gain cognitive control by stopping and recognizing persuasive attempts (i.e., stop-and-think responses, see Rozendaal, Lapierre, van Reijmersdal, & Buijzen, 2011). Given the phenomenon of phubbing in romantic relationships, human communication researchers may incorporate RSD theorizing to explain relationship satisfaction and relational health. Also, in health communication research, RSD may be able to predict information management and anxiety in illness contexts (Kuang & Wilson, 2017). The RSD concept can form the basis of interventions aimed at preventing excessive smartphone use and promoting digital well-being. From a dual-systems perspective, interventions are most effective if they simultaneously attempt to change people's reasoned beliefs and impulsive influences on behavior (Deutsch & Strack, 2020). In this context, the RSD provides a valuable addition to design such interventions by providing important insights into the reflective system and how reflective cognitions may prevent excessive smartphone use, perceived information overload, and social availability norms. Together with treatments directed at changing impulsive processes associated with tempting stimuli like social media applications, the RSD concept can offer new possibilities to prevent excessive smartphone use. Finally, and more generally, research on uses and gratifications may use the RSD concept to further conceptualize avoidance behavior with respect to media choice, that is, to *not* select media content in order to escape from content experienced as unpleasant (Perse, 1998).

7.2. Limitations

Important shortcomings have to be mentioned. First, we relied on self-reports when measuring RSD. Researchers suggest that reporting behavioral intentions can be a good estimate of actual behavior (Webb & Sheeran, 2006). Nevertheless, RSD measures should be validated with applications that control actual use. Second, cross-cultural validation of the RSD concept is warranted. Third, regarding methodological limitations, one clear disadvantage is the lack of causal evidence in our studies. Although we could draw directionality and temporal order of the RSD scale as a predictor of excessive use, information overload, and social availability norm, we did not establish causal order. Experimental research is therefore needed. Additionally, we did not find an acceptable model fit from the confirmatory factor analysis in the third study and thus added a fourth study confirming the 5-item scale. Additional research in other contexts is needed to determine if the five-item or six-item scale is superior. Fourth, we measured some of the concepts used for validation with a selected set of key items only, calling for additional data. For example, future research should include impulsivity traits or impulsive types of mobile phone use to provide further discriminant validity of the reflective dimension in our scale. Finally, some RSD items refer to certain situations, others to general assessments of mobile phone attachment. Clearly, additional research is needed, potentially separating or revising these different aspects.

8. Conclusion

With the smartphone as the constant companion in most people's lives, the necessity to reflect on one's smartphone use to ensure optimal digital well-being (Vanden Abeele, 2020) is bigger than ever before. In this paper, we outlined a new concept and a measurement for it, RSD, to address the hitherto ignored importance of the reflective system when using the smartphone. The RSD concept should be used in future research along with constructs tapping the impulsive aspect of smartphone use. Such a stream of research could not only lead to a more complete and more nuanced picture of the antecedents and consequences of smartphone use, but also helps society to better reflect on the permanent omnipresence of the smartphone in our daily lives.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2021.107078.

Author contributions

Jörg Matthes: Conceptualization, Supervision, Methodology, Writing – original draft. **Kathrin Karsay**: Conceptualization, Methodology, Writing – original draft. **Melanie Hirsch**: Writing – original draft. **Anja Stevic**: Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Desirée Schmuck**: Conceptualization, Methodology, Writing – review & editing.

References

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational Behavior and Human Decision Processes, 50*, 248–287. https://doi.org/10.1016/0749-5978(91)90022-L

Barley, S. R., Meyerson, D. E., & Grodal, S. (2011). E-mail as a source and symbol of stress. *Organization Science, 22*, 887–906. https://doi.org/10.1287/orsc.1100.0573

Baumeister, R. F. (2007). Self-regulation. In R. F. Baumeister, & K. D. Vohs (Eds.), *Encyclopedia of social psychology* (pp. 841–844). Thousand Oaks, Calif: Sage Publications Inc.

Bayer, J. B., Dal Cin, S., Campbell, S. W., & Panek, E. (2016). Consciousness and self-regulation in mobile communication. *Human Communication Research, 42*, 71–97. https://doi.org/10.1111/hcre.12067

Berger, S., Wyss, A. M., & Knoch, D. (2018). Low self-control capacity is associated with immediate responses to smartphone signals. *Computers in Human Behavior, 86*, 45–51. https://doi.org/10.1016/j.chb.2018.04.031

Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology and Behavior, 8*, 39–51. https://doi.org/10.1089/cpb.2005.8.39

Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews, 8*, 299–307. https://doi.org/10.2174/157340012803520522

Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. (2015). Can disordered mobile phone uue be considered a behavioral addiction? An update on current evidence and a comprehensive model for future research. *Current Addictions Report, 2*, 156–162. https://doi.org/10.1007/s40429-015-0054-y

Butt, S., & Phillips, J. G. (2008). Personality and self reported mobile phone use. *Computers in Human Behavior, 24*, 346–360. https://doi.org/10.1016/j.chb.2007.01.019

Byrne, B. M. (2001). Structural equation modeling with AMOS, EQS, and LISREL: Comparative approaches to testing for the factorial validity of a measuring instrument. *International Journal of Testing, 1*, 55–86. https://doi.org/10.1207/s15327574ijt0101_4

Caplan, S. E. (2010). Theory and measurement of generalized problematic internet use: A two-step approach. *Computers in Human Behavior, 26*, 1089–1097. https://doi.org/10.1016/j.chb.2010.03.012

Carver, C. S., & Scheier, M. F. (1998). *On the self-regulation of behavior*. Cambridge: Cambridge University Press.

Chatterjee, S. (2020). Antecedents of phubbing: From technological and psychological perspectives. *Journal of Systems and Information Technology, 22*(2), 161–178. https://doi.org/10.1108/JSIT-05-2019-0089

Cheever, N. A., Rosen, L. D., Carrier, L. M., & Chavez, A. (2014). Out of sight is not out of mind: The impact of restricting wireless mobile device use on anxiety levels among low, moderate and high users. *Computers in Human Behavior, 37*, 290–297. https://doi.org/10.1016/j.chb.2014.05.002

Chin, E., Felt, A. P., Sekar, V., & Wagner, D. (2012). Measuring user confidence in smartphone security and privacy. *SOUPS 2012 - Proceedings of the Eighth Symposium on Usable Privacy and Security*, 1–16. https://doi.org/10.1145/2335356.2335358

Chotpitayasunondh, V., & Douglas, K. M. (2016). How "phubbing" becomes the norm: The antecedents and consequences of snubbing via smartphone. *Computers in Human Behavior, 63*, 9–18. https://doi.org/10.1016/j.chb.2016.05.018

Clark, J. L., Algoe, S. B., & Green, M. C. (2018). Social network sites and well-being: The role of social connection. *Current Directions in Psychological Science, 27*, 32–37. https://doi.org/10.1177/0963721417730833

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.

Contractor, A. A., Weiss, N. H., Tull, M. T., & Elhai, J. D. (2017). PTSD's relation with problematic smartphone use: Mediating role of impulsivity. *Computers in Human Behavior, 75*, 177–183. https://doi.org/10.1016/j.chb.2017.05.018

Deters, F. G., & Mehl, M. R. (2013). Does posting Facebook status updates increase or decrease loneliness? An online social networking experiment. *Social Psychological and Personality Science, 4*, 579–586. https://doi.org/10.1177/1948550612469233

Deutsch, R., & Strack, F. (2020). Changing behavior using the reflective-impulsive model. In M. S. Hagger, L. D. Cameron, K. Hamilton, N. Hankonen, & T. Lintunen (Eds.), *The handbook of behavior change* (pp. 164–177). Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/9781108677318.012.

Diefenbach, S., & Borrmann, K. (2019). The smartphone as a pacifier and its consequences: Young adults' smartphone usage in moments of solitude and correlations to self-reflection. In *2019 CHI conference on human factors in computing systems proceedings (CHI 2019), glasgow, scotland, UK. ACM, New York, NY, USA* (pp. 1–14). https://doi.org/10.1145/3290605.3300536

Dienlin, T., & Metzger, M. J. (2016). An extended privacy calculus model for SNSs: Analyzing self-disclosure and self-withdrawal in a representative U.S. sample. *Journal of Computer-Mediated Communication, 21*, 368–383. https://doi.org/10.1111/jcc4.12163

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society, 20*, 325–344. https://doi.org/10.1080/01972240490507974

Gerbing, D. W., & Hamilton, J. G. (1996). Viability of exploratory factor analysis as a precursor to confirmatory factor analysis. *Structural Equation Modeling, 3*(1), 62–72. https://doi.org/10.1080/10705519609540030

Grant, A. M., Franklin, J., & Langford, P. (2002). The self-reflection and insight scale: A new measure of private self-consciousness. *Social Behavior and Personality, 30*, 821–836. https://doi.org/10.2224/sbp.2002.30.8.821

Hall, J. A., Baym, N. K., & Miltner, K. M. (2014). Put down that phone and talk to me: Understanding the roles of mobile phone norm adherence and similarity in relationships. *Mobile Media & Communication, 2*, 134–153. https://doi.org/10.1177/2050157913517684

Hefner, D., Knop, K., & Klimmt, C. (2018). Being mindfully connected: Responding to the challenges of adolescents living in a POPC world. In P. Vorderer, D. Hefner, L. Reinecke, & C. Klimmt (Eds.), *Permanently online, permanently connected. Living and communicating in a POPC world* (pp. 176–187). New York: Routledge.

Hefner, D., Knop, K., Schmitt, S., & Vorderer, P. (2019). Rules? Role model? Relationship? The impact of parents on their children's problematic mobile phone involvement. *Media Psychology, 22*, 82–108. https://doi.org/10.1080/15213269.2018.1433544

Hofmann, W., Friese, M., & Strack, F. (2009). Impulse and self-control from a dual-systems perspective. *Perspectives on Psychological Science, 4*, 162–176. https://doi.org/10.1111/j.1745-6924.2009.01116.x

Hsu, C.-L., & Lin, J. C.-C. (2018). Exploring factors affecting the adoption of internet of things services. *Journal of Computer Information Systems, 58*, 49–57. https://doi.org/10.1080/08874417.2016.1186524

John, O. P., & Benet-Martinez, V. (2000). Measurement: Reliability, construct validation, and scale construction. In H. T. Reis, & C. M. Judd (Eds.), *Handbook of research methods in personality and social psychology* (pp. 339–369). New York: CUP.

Karr-Wisniewski, P., & Lu, Y. (2010). When more is too much: Operationalizing technology overload and exploring its impact on knowledge worker productivity. *Computers in Human Behavior, 26*, 1061–1072. https://doi.org/10.1016/j.chb.2010.03.008

Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of Conflict Resolution, 2*, 51–60. https://doi.org/10.1177/002200275800200106

Kim, D., Lee, Y., Lee, J., Nam, J. K., & Chung, Y. (2014). Development of Korean smartphone addiction proneness scale for youth. *PLoS One, 9*, Article e97920. https://doi.org/10.1371/journal.pone.0097920

King, A. L. S., Valença, A. M., Silva, A. C. O., Baczynski, T., Carvalho, M. R., & Nardi, A. E. (2013). Nomophobia: Dependency on virtual environments or social phobia? *Computers in Human Behavior, 29*, 140–144. https://doi.org/10.1016/j.chb.2012.07.025

King, A. L. S., Valença, A. M., Silva, A. C., Sancassiani, F., Machado, S., & Nardi, A. E. (2014). "Nomophobia": Impact of cell phone use interfering with symptoms and emotions of individuals with panic disorder compared with a control group. *Clinical Practice and Epidemiology in Mental Health: CP & EMH, 10*, 28. https://doi.org/10.2174/1745017901410010028

Kline, R. B. (1998). *Principles and practice of structural equation modeling*. London: Guilford.

Knop, K., Hefner, D., Schmitt, S., & Vorderer, P. (2015). *Mediatisierung mobile Handy- und mobile Internetnutzung von Kindern und Jugendlichen [Mediatization of mobile phone and mobile Internet use by children and young people*. Leipzig: Vistas.

Kolb, D. G., Caza, A., & Collins, P. D. (2012). States of connectivity: New questions and new directions. *Organization Studies, 33*, 267–273. https://doi.org/10.1177/0170840611431653

Kuang, K., & Wilson, S. R. (2017). A meta-analysis of uncertainty and information management in illness contexts. *Journal of Communication, 67*, 378–401. https://doi.org/10.1111/jcom.12299

Kwon, M., Lee, J.-Y., Won, W.-Y., Park, J.-W., Min, J.-A., Hahn, C., et al. (2013). Development and validation of a smartphone addiction scale (SAS). *PLoS One, 8*. https://doi.org/10.1371/journal.pone.0056936

LaRose, R., Connolly, R., Lee, H., Li, K., & Hales, K. D. (2014). Connection overload? A cross cultural study of the consequences of social media connection. *Information Systems Management, 31*, 59–73. https://doi.org/10.1080/10580530.2014.854097

Lee, Y.-K., Chang, C.-T., Lin, Y., & Cheng, Z.-H. (2014). The dark side of smartphone usage: Psychological traits, compulsive behavior and technostress. *Computers in Human Behavior, 31*, 373–383. https://doi.org/10.1016/j.chb.2013.10.047

Lee, A. R., Son, S.-M., & Kim, K. K. (2016). Information and communication technology overload and social networking service fatigue: A stress perspective. *Computers in Human Behavior, 55*, 51–61. https://doi.org/10.1016/j.chb.2015.08.011

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2003). Habit in the context of IS continuance: Theory extension and scale development. In *ECIS 2003 proceedings* (Vol. 90). Retrieved from https://aisel.aisnet.org/ecis2003/90.

Lin, Y.-H., Lin, Y.-C., Lee, Y.-H., Lin, P.-H., Lin, S.-H., Chang, L.-R., et al. (2015). Time distortion associated with smartphone addiction: Identifying smartphone addiction via a mobile application (App). *Journal of Psychiatric Research, 65*, 139–145. https://doi.org/10.1016/j.jpsychires.2015.04.003

Mai, L. M., Freudenthaler, R., Schneider, F. M., & Vorderer, P. (2015). "I know you've seen it!" Individual and social factors for users' chatting behavior on Facebook. *Computers in Human Behavior, 49*, 296–302. https://doi.org/10.1016/j.chb.2015.01.074

Mani, Z., & Chouk, I. (2017). Drivers of consumers' resistance to smart products. *Journal of Marketing Management, 33*, 76–97. https://doi.org/10.1080/0267257X.2016.1245212

Meerkerk, G.-J., Van Den Eijnden, R. J. J. M., Vermulst, A. A., & Garretsen, H. F. L. (2009). The compulsive internet use scale (CIUS): Some psychometric properties. *CyberPsychology and Behavior, 12*, 1–6. https://doi.org/10.1089/cpb.2008.0181

Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences, 116*(21), 10226–10228. https://doi.org/10.1073/pnas.1902058116

Perse, E. M. (1998). Implications of cognitive and affective involvement for channel changing. *Journal of Communication, 48*(3), 4968. https://doi.org/10.1111/j.1460-2466.1998.tb02759.x

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*, 1–36. https://doi.org/10.18637/jss.v048.i02

Rozendaal, E., Lapierre, M. A., van Reijmersdal, E. A., & Buijzen, M. (2011). Reconsidering advertising literacy as a defense against advertising effects. *Media Psychology, 14*, 333–354. https://doi.org/10.1080/15213269.2011.620540

Russo, M., Ollier-Malaterre, A., & Morandin, G. (2019). Breaking out from constant connectivity: Agentic regulation of smartphone use. *Computers in Human Behavior, 98*, 11–19. https://doi.org/10.1016/j.chb.2019.03.038

Schmitt, J. B., Debbelt, C. A., & Schneider, F. M. (2018). Too much information? Predictors of information overload in the context of online news exposure. *Information, Communication and Society, 21*, 1151–1167. https://doi.org/10.1080/1369118X.2017.1305427

Schnauber-Stockmann, A., Meier, A., & Reinecke, L. (2018). Procrastination out of habit? The role of impulsive versus reflective media selection in procrastinatory media use. *Media Psychology, 21*, 640–668. https://doi.org/10.1080/15213269.2018.1476156

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory analysis results: A review. *The Journal of Educational Research, 99*, 323–337. https://doi.org/10.3200/JOER.99.6.323-338

Sherman, J. W., Gawronski, B., Gonsalkorale, K., Hugenberg, K., Allen, T. J., & Groom, C. J. (2008). The self-regulation of automatic associations and behavioral impulses. *Psychological Review, 115*(2), 314–335. https://doi.org/10.1037/0033-295X.115.2.314

Strack, F., & Deutsch, R. (2004). Reflective and impulsive determinants of social behavior. *Personality and Social Psychology Review, 8*, 220–247. https://doi.org/10.1207/s15327957pspr0803_1

Sutanto, J., Palme, E., Tan, C.-H., & Phang, C. W. (2013). Addressing the personalization-privacy paradox: An empirical assessment from a field experiment on smartphone users. *MIS Quarterly, 37*, 1141–1164. https://doi.org/10.25300/MISQ/2013/37.4.07

Sutton, T. (2017). Disconnect to reconnect: The food/technology metaphor in digital detoxing. *First Monday, 22*. https://doi.org/10.5210/fm.v22i6.7561

Tams, S., Legoux, R., & Léger, P.-M. (2018). Smartphone withdrawal creates stress: A moderated mediation model of nomophobia, social threat, and phone withdrawal context. *Computers in Human Behavior, 81*, 1–9. https://doi.org/10.1016/j.chb.2017.11.026

Thomée, S., Härenstam, A., & Hagberg, M. (2011). Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults - a prospective cohort study. *BMC Public Health, 11*, 1–11. https://doi.org/10.1186/1471-2458-11-66

Tran, J. A., Yang, K. S., Davis, K., & Hiniker, A. (2019). Modeling the engagement-disengagement cycle of compulsive phone use. In *CHI conference on human factors in computing systems proceedings (CHI 2019), may 4–9, 2019*. Glasgow, Scotland UK. New York: ACM. https://doi.org/10.1145/3290605.3300542.

Turel, O., & Qahri-Saremi, H. (2016). Problematic use of social networking sites: Antecedents and consequence from a dual-system theory perspective. *Journal of Management Information Systems, 33*, 1087–1116, 07421222.2016.1267529.

Van Deursen, A. J. A. M., Bolle, C. L., Hegner, S. M., & Kommers, P. A. M. (2015). Modeling habitual and addictive smartphone behavior: The role of smartphone usage types, emotional intelligence, social stress, self-regulation, age, and gender. *Computers in Human Behavior, 45*, 411–420. https://doi.org/10.1016/j.chb.2014.12.039

Van Koningsbruggen, G. M., Hartmann, T., & Du, J. (2018). Always on? Explicating impulsive influences on media use. In P. Vorderer, D. Hefner, L. Reinecke, & C. Klimmt (Eds.), *Permanently online, permanently connected: Living and communicating in a POPC world* (pp. 51–60). New York: Routledge.

Vanden Abeele, M. M. (2020). *Digital wellbeing as a dynamic construct. Communication Theory*. https://doi.org/10.1093/ct/qtaa024

Vohs, D. K. (2006). Self-regulatory resources power the reflective system: Evidence from five domains. *Journal of Consumer Psychology, 16*, 217–223. https://doi.org/10.1207/s15327663jcp1603_3

Vorderer, P., Hefner, D., Reinecke, L., & Klimmt, C. (2018). Permanently online and permanently connected: A new paradigm in communication research? In P. Vorderer, D. Hefner, L. Reinecke, & C. Klimmt (Eds.), *Permanently online, permanently connected: Living and communicating in a POPC world* (pp. 3–9). NY: Routledge.

Wang, T., Duong, T. D., & Chen, C. C. (2016). Intention to disclose personal information via mobile applications: A privacy calculus perspective. *International Journal of Information Management, 36*, 531–542. https://doi.org/10.1016/j.ijinfomgt.2016.03.003

Wang, J.-L., Gaskin, J., Rost, D. H., & Gentile, D. A. (2018). The reciprocal relationship between passive social networking site (SNS) usage and users' subjective well-being. *Social Science Computer Review, 36*, 511–522. https://doi.org/10.1177/0894439317721981

Wang, Y., Meister, D., & Gray, P. (2013). Social influence and knowledge management systems use: Evidence from panel data. *MIS Quarterly, 37*, 299–313. https://doi.org/10.25300/MISQ/2013/37.1.13

Webb, T. L., & Sheeran, P. (2006). Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological Bulletin, 132*, 249–268. https://doi.org/10.1037/0033-2909.132.2.249

Wilmer, H. H., & Chein, J. M. (2016). Mobile technology habits: Patterns of association among device usage, intertemporal preference, impulse control, and reward sensitivity. *Psychonomic Bulletin & Review, 23*, 1607–1614. https://doi.org/10.3758/s13423-016-1011-z

Yang, C., & Bradford Brown, B. (2016). Online self-presentation on Facebook and self development during the college transition. *Journal of Youth and Adolescence, 45*, 402–416. https://doi.org/10.1007/s10964-015-0385-y

Yao, M. Z., & Zhong, Z.-J. (2014). Loneliness, social contacts and internet addiction: A cross-lagged panel study. *Computers in Human Behavior, 30*, 164–170. https://doi.org/10.1016/j.chb.2013.08.007

Yildirim, C., & Correia, A.-P. (2015). Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire. *Computers in Human Behavior, 49*, 130–137. https://doi.org/10.1016/j.chb.2015.02.059

Young, K. S. (1996). Psychology of computer use: XL. Addictive use of the internet: A case that breaks the stereotype. *Psychological Reports, 79*, 899–902. https://doi.org/10.2466/pr0.1996.79.3.899