The Relationship Between Instant Gratification and Actual Social Media Use

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Abstract

Social media have become ubiquitous in the lives of many young adults. The constant and easy access to 'instant rewards' and the potential adverse consequences of its overuse, have motivated individual difference studies with respect to social media-related behaviors. The current study reports on an online survey that explored whether differences in seeking instant gratification are related to young adults' habits of social media use. The latter were assessed both through self-report and actual phone use data. Moreover, it was explored whether this relationship is moderated by young adults' self-control ability (assessed both through self-report and objective task performance) and/or their ability to refrain from using social media. Finally, we assessed individuals' self-reported style of social media use (on a continuum from passive to active use) to explore its role in the relationship between instant gratification and social media use. The results of this relationship were, in part, in the opposite direction to what was expected. Specifically, the higher a users' preference for instant gratification, the *less* was her/his time spent on Instagram. There was no moderating effect of self-control and social media self-control failure, nor was there mediating effect of style of social media use on this relationship. These findings are critically discussed in line with previous work, and suggestions for future directions are provided.

Keywords: instant gratification, reward, self-control, social media, passive and active use, refrain-from-blinking task

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The Relationship Between Instant Gratification and Actual Social Media Use

The omnipresence of social media platforms (SMPs; e.g., Facebook and Instagram) that smartphones give continuous access to, has made it easy to acquire information and interact with other people anytime and anywhere (Vanden Abeele, 2020). Recent estimates indicate that 90% of 18-29 year olds in the U.S. actively use at least one social media (SM) app (*Social Media Fact Sheet*, 2019). More than half of 14-22 year olds visit SMPs multiple times a day and spend on average about 1h per day using them (Rideout & Fox, 2018). Furthermore, with the advent of the COVID-19 pandemic and its lockdowns, time spent on SM has even increased (Paschke et al., 2021). As social media use (SMU) increases, so too do concerns about social media (over-)use and its implications for human cognition.

Push notifications promising social attention, instant access to information, and other types of highly desirable SMU rewards make it difficult to refrain from using SM, even when its use conflicts with other (more long-term) goals or ongoing tasks at that moment (e.g., focused driving). The human mind prioritizes rewards even if this prioritization has negative consequences (Caird et al., 2014; Rusz et al., 2020). Also, SMU may negatively affect one's general cognitive functioning, as has been claimed for example with respect to attention, memory, and decision-making processes (see Wilmer et al. 2017 for a review). Therefore, given the ever-increasing time spent on SM and the potential risk of overuse, it is essential to look at individual differences in cognitive functioning that may be associated with SM-related behaviors. In this study, we will look at individual differences in preference for instant gratification (i.e., the preference for smaller and immediate rewards over more significant and delayed rewards) and its relationship with SM usage via the smartphone.

Neuroimaging research suggests that *actively* using SM (e.g., receiving Likes and posting one's content) is associated with increased activity in the brain's reward system (Meshi et al., 2013, 2015; Montag et al., 2017; Sherman et al., 2016, 2018). Even though individuals may not always self-report to engage with media specifically for pursuing gratification (Zhang & Zhang, 2012), the search for instant gratification can be theorized to play a role in SM engagement. A very recent study that assessed real-world SMU data showed that engagement with certain behaviors in SM reflects a reward-based behavior. Specifically, social media users with a higher history of social rewards (Likes) rates on their past posts showed a shorter latency to the next post than users with a lower history of social rewards (Lindström et al., 2021). Hence, SM posting behavior followed the principles of reinforcement learning, with reward-seeking as a core drive in engagement with SM. Accordingly, social media users who have a natural tendency to prefer instant rewards over larger, delayed ones (and/or social media users who eventually increased their preference for instant gratification specifically due to intensive usage of SM), may be at higher risk for SM overuse — regardless of the potential adverse consequences of its overuse.

Previous correlational studies showed a positive relationship between SMU via the smartphone and users' preference for instant gratification. For example, Schulz van Endert and Mohr (2020) found that increased SM screen time is associated with users' higher preference for instant rewards. In a more narrow scope, Delaney et al. (2018) found that users with a higher Facebook addiction score tend to prefer instant gratification (as in other substance and behavioral addictions). In other studies assessing overall smartphone usage, it was similarly found that heavier self-reported engagement correlates with discounting future rewards more heavily (Frost et al., 2019; Hadar et al., 2017; Tang et al., 2017; Wilmer et al., 2019; Wilmer & Chein, 2016).

Studies have investigated whether individual differences in self-control play a role in media engagement. Self-control refers to individuals' ability to override or alter one's dominant response tendencies (Schmeichel & Zell, 2007). Having higher levels of self-control might help control the (overly extensive) use of SM, as checking SM via the smartphone is often the result of habitual behavior and automatic impulses (Kim et al., 2016). Moreover, a higher preference for instant gratification may also reflect difficulties in self-control, as controlling one's impulsive choices would result in a larger, even though delayed, reward (Moreira & Barbosa, 2019). Indeed, Wilmer and Chein (2016) found that heavier self-reported engagement with the smartphone is related to weaker self-control, which mediates the relationship between instant gratification and self-reported smartphone use. However, these findings failed to replicate in subsequent studies (e.g., Wilmer et al., 2019). More recently, Schulz van Endert and Mohr (2020) found that self-reported self-control was negatively correlated with net screen time, but the previous mediating effect of self-control did not replicate. Thus, future research is needed to understand whether and how self-control (both self-reported and objectively measured) is at play in the relationship between instant gratification and SMU.

As outlined above, previous findings have provided initial evidence on the associations between SM usage via smartphones, instant gratification, and self-control. However, they did not come without limitations, which may, on the one hand, compromise the validity of the findings and, on the other hand, restrain the understanding of the relationship between individual difference factors and SMU. Most previous research has relied solely on self-reported measures of technology engagement, which has limitations in determining actual use (Parry et al., 2020). A similar case can be made with respect to (solely) using self-report measures of self-control, as individuals have limited knowledge of their own traits or abilities (Schmeichel & Zell, 2007). In addition, while different styles of SMU have been described (ranging from active use such as in posting and commenting, to more passive use such as in scrolling and browsing; (Escobar-Viera et al., 2018), these styles have not been considered before. Researchers have limited their assessment of SMU to the frequency of usage, but the underlying style of social media use may be highly relevant, especially since different styles of use lead to different outcomes in social media users' psychological functioning (Escobar-Viera et al., 2018; Hanley et al., 2019). Indeed, the type and intensity of rewards obtained via SMU may differ between different styles of SMU. Future research has to move beyond the current state-of-the-art, and zoom in on the type of activities performed during SMU (Odgers et al., 2020; Orben, 2020; Pontes, 2020).

The current study aims to understand whether differences in instant gratification relate to an individual's SMU intensity, considering the above-mentioned limitations and inconsistent findings from previous work. First, we will assess actual social media use by collecting mobile log data (Ohme et al., 2021). Secondly, in addition to self-report assessment, we will administer a performance-based measure of self-control, i.e., the refrain-from-blinking task (Schmeichel & Zell, 2007). Third, a more dedicated measure of trait self-control in the specific context of SMU will be used, i.e., the self-control social media failure (Du et al., 2018). Finally, we will assess participants' style of social media use (measured in a continuum from passive to active use) and explore whether it impacts the relationship between instant gratification and actual social media use. Overall, the following research questions are postulated: *Is instant gratification related to actual social media use (RQ1)?; Is this relationship moderated by self-control and/or social media self-control failure (RQ2)?; and finally, is this relationship mediated by users' style of social media use (RQ3)?*

Theoretical Framework

Social Media and Rewards

Social media platforms (SMPs) are defined as digital services that let users connect, join communities, share media, and update status (Boyd & Ellison, 2007). Examples of SMPs are Facebook, Instagram, Twitter, YouTube, and, more recently, TikTok. These are among the most used SMPs by young adults in wealthy countries (de Best, 2019); therefore, these are also the platforms of interest in the current study. Daily SMU is an undeniable phenomenon of the twenty-first century, most in part due to smartphone technology which has made it easy to access SMPs anytime and anywhere (Vanden Abeele, 2020). Unsurprisingly, this tremendous worldwide success of SMPs has intrigued researchers on what drives people to use, sometimes overuse, SMPs in the first place. Among the many motives that might lead people to use SMPs (e.g., to connect with others, and to carry on the impression we make on others (Meshi et al., 2015)), is that people may engage with SMPs to pursue gratification (Lindström et al., 2021).

SMPs are an omnipresent source of instant rewards, mainly social rewards. These can assume many forms, including positive feedback like Likes, social reinforcements in the form of shares, or following requests. Humans have an intrinsic motivation to belong and to connect with others (Baumeister & Leary, 1995; Maslow, 1943). SMPs simply take advantage of these pre-existing social drives by providing the medium for people to gratify those needs. For example, by engaging in one of the five key SM behaviors — i.e., to broadcast information (Meshi et al., 2015) — a user can share an updated photo of theirs and instantly receive social feedback on it, which often comes through the form of a Like or a positive comment. This way, the social needs of both intervenients are being gratified, and users can even afford social comparison — by contrasting the number of Likes received in their photos with the number of

Likes of other users' photos within the same network (Meshi et al., 2015). This is a typical example of how SMPs engine social dynamics online.

But there are other multiple possibilities for users to afford a rewarding experience while using SMPs, and it seems that those activities indeed activate primarily reward-related brain regions. Neuroscience research has shown that a series of events taking place while interacting with SMPs are associated with increased activity in the brain's reward center (Meshi et al., 2013, 2015; Montag et al., 2017; Sherman et al., 2016, 2018). For example, Sherman et al. (2016) found in an experimental setting that receiving Likes on social media users' posts is responsible for activating the nucleus accumbens (NAc) — a brain structure with an essential role in the brain's reward processing system; which was also found to respond to monetary rewards (Rademacher et al., 2014). More recently, Sherman et al. (2018) found that not only receiving Likes activates the neural circuitry associated with reward processing, but giving Likes on others' content has a similar neural response. Therefore, it is becoming evident that SMU provides users with instant access and an endless supply of rewards, which may play an important role in engagement with the SMPs.

Reward Learning

SMU might relate to Reinforcement Learning Theory (Sutton & Barto, 2018). Rewarding the user when (s)he engages with SM (e.g., showing new Likes on users' new posts) can work as a *positive reinforcement* to keep users coming back. According to Skinner's pigeon experiments, the reinforcement of a behavior is conditioned by not only the received rewards but also by the schedules at which the rewards are provided. The behavior is strengthened if the rewards are delivered in a *variable-ratio* schedule of reinforcement, i.e., rewarding after an unpredictable number of responses (Skinner, 1948). This translates well to SMU, where Likes (i.e., rewards) come in at unpredictable moments and in unpredictable flow after a post (i.e., behavior). Variable-ratio schedules are known to lead to a high, continuous rate of responding. People tend to increase the rate of responses (e.g., checking SM) when rewards (e.g., Likes) are delivered at unpredictable times (Skinner, 1948). Therefore, even though individuals did not self-report to engage with media to pursue gratification (Zhang & Zhang, 2012), there are reasons to believe that it may indeed play a role, at least, at an unconscious level (Lindström et al., 2021).

Lindström et al. (2021), who analyzed time-stamps of posts and Likes from more than two thousand users, found that people spaced their posts in a way that maximizes their average rate of rewards. Participants posted more frequently after a high rate of Likes on their previous posts, and less frequently when they received fewer Likes. Moreover, in a follow-up experiment, in which participants received different average amounts of Likes on an Instagram-like platform, researchers could verify the causal effect of social rewards on how often people post. So, this suggests that people engage with SM with the expectation to be immediately rewarded. Indeed, social media companies are very aware of these reward learning mechanisms (Harris, 2019). For example, Twitter was accused of delaying the delivery of notifications to users at irregular intervals on purpose (Staff, 2017). Another example, Jonathan Badeen, a co-founder of Tinder, acknowledged in a recent interview that Tinder's algorithms were designed with Skinner's operant conditioning and schedules of reinforcement in mind (Jo Sales, 2018).

Instant Gratification and Individual Differences

Individuals are frequently faced with the difficult task of choosing between a smaller, instant reward and a larger, later reward. An example is whether to spend leisure time on an activity that is instantly rewarding, such as checking SM (Meshi et al., 2015), or to spend it on any other activity with potentially greater subjective value in the future (e.g., studying for an exam). In the current study, the preference for the smaller, instant reward over the future, larger reward is referred to as preference for *instant gratification*. In general, humans (and non-human animals) have a tendency to prefer instant gratification, regardless of its well-known widespread consequences for the individual and the wider society in healthy and economic terms (Moreira & Barbosa, 2019).

However, a growing body of literature suggests that instant gratification varies largely in magnitude across individuals. These individual differences in preference for instant gratification are, for the most part, stable over time and even in part heritable (Keidel et al., 2021). They lead to differences in outcomes that are somehow associated with one's preference for instant gratification (Keidel et al., 2021). Therefore, with SM being shown to be a source of instant gratification, and engagement with SM to be driven by rewards seeking, it is reasonable to expect that individual differences in preference for instant gratification will reflect individual differences in SMU.

To assess individual differences in participants' preference for instant gratification in the current study, a delay discounting task i.e., the 27-item Monetary Choice Questionnaire was used (27-item MCQ). It has been previously used by researchers in the context of actual social media use (Schulz van Endert & Mohr, 2020). Schulz van Endert and Mohr (2020) found that social media users with a lower proportion of *LDR* choices (i.e., participants' number of choices, in percentage, towards the larger, delayed monetary rewards in the MCQ) are more likely to spend more time on SM. Therefore, the first hypothesis is formulated:

H1: There is a positive correlation between instant gratification and actual social media use, which will show as a negative correlation between the LDR Proportion and actual social media use (screen time and pickups).

Self-control

A recent review study that compiled the underlying variables of individual differences in preference for instant gratification showed that, among many other variables, a consistently low level of self-control is often related to preference for instant gratification (Keidel et al., 2021). This is not surprising, as conceptually speaking, the definitions of self-control and instant gratification (provided above) are very similar. Self-control is defined as the individuals' ability to override or alter one's dominant response tendencies (Schmeichel & Zell, 2007). Deciding between a smaller, instant reward and a larger but delayed reward, certainly demands one's ability to self-control and override what is a general tendency for instant gratification. Indeed, prior research has shown that individuals with a higher propensity for instant gratification have lower levels of self-control, even though correlations are, on average, not very high (Keidel et al., 2021; Schulz van Endert & Mohr, 2020; Wilmer & Chein, 2016). In addition, increased capacities to override one's dominant response tendencies might help to refrain from using SM, as its use is oftentimes the result of habitual behavior and automatic impulses (Kim et al., 2016). Having an instant and often-present rewarding option to escape from a (maybe not so instant rewarding) ongoing task, might present an increased challenge to one's ability to self-control, mainly for those who have a higher preference for instant gratification. Therefore, it is likely that social media users with lower levels of self-control have more difficulty resisting temptations to use SM and a higher preference for instant gratification.

Research on the relationship between self-control, instant gratification, and media engagement is scarce and inconclusive. Schulz van Endert and Mohr (2020) found that self-reported self-control (assessed with the Brief Self-control Scale; BSCS; Tangney et al., 2004) was negatively correlated with net screen time. However, the finding did not replicate with a performance-based self-control measure (i.e., the Go/No-Go task). Moreover, there was no mediating effect of self-control on the relationship between instant gratification (assessed with the LDR proportion) and net screen time, even though Wilmer and Chein (2016) did report on such mediation for smartphone use. Indeed, the latter did not replicate in a more recent study by Wilmer et al. (2019). Hence, the current study will look further into these relationships. A specific measure of performance-based self-control — namely, the ability to inhibit eye blinks — was selected to complement a self-report measure of self-control because the two were shown in previous work to correlate (Schmeichel & Zell, 2007), in contrast to other performance-based measures of self-control such as the Go/No-Go task (Dreves et al., 2020). The following hypotheses are formulated:

H2a: The relationship between instant gratification and actual social media use is stronger for users with low than high self-reported self-control.

H2b: The relationship between instant gratification and actual social media use is stronger for users with high than low performance-based self-control.

Social Media Self-control Failure

The above self-report and performance-based measures aim to tap into general, context-independent self-control. To further our understanding of the role of self-control in the specific context of SMU, we will use an additional measure of self-reported self-control that zooms in how often social media users fail to resist social media desires i.e., Social Media Self-control Failure (SMSCF; Du et al., 2018). This novel measure of failure to control one's SMU was shown to (highly) correlate with the standard measure of self-control i.e., BSCS. In other words, social media users with high self-reported self-control fail less often to resist using SM when its use conflicts with other goals (Du et al., 2018). Thus, expectations and foundational theory for the role of self-reported self-control in the relationship between instant gratification and SMU should hold for the role of SMSCF in this same relationship. Therefore, it is hypothesized:

H3: The relationship between instant gratification and actual social media use is stronger for users with high than low social media self-control failure.

Style of Social Media Use

Finally, we elaborate on the role of the style of social media use on the relationship between instant gratification and SMU. While using SM one can perform a variety of behaviors (Meshi et al., 2015), users can be distinguished from each other on *how* they generally tend to use SM on a continuum from passive to active use. Active SMU refers to activities that imply interacting with others and their content (e.g., commenting on a post), whereas passive use refers to entirely non-interactive activities (e.g., scrolling through the newsfeed) (Petropoulos Petalas et al., 2021).

Evidence to date suggests that users' active use of SM is typically associated with positive psychosocial outcomes (e.g., well-being and social satisfaction) when compared to passive use (Shaw et al., 2021). Therefore, scholars often encourage social media users to make active use of SMPs (e.g., Hanley et al., 2019). However, considering the reward-driven hypothesis on SM engagement (discussed above), one might question whether advocating for active use of SM over a passive use, does also hold when relating style of social media usage to one's preference for instant gratification and time spent on SM. To our knowledge, these associations have not been considered before. However, they might be highly relevant given the previous findings on users' psychological functioning.

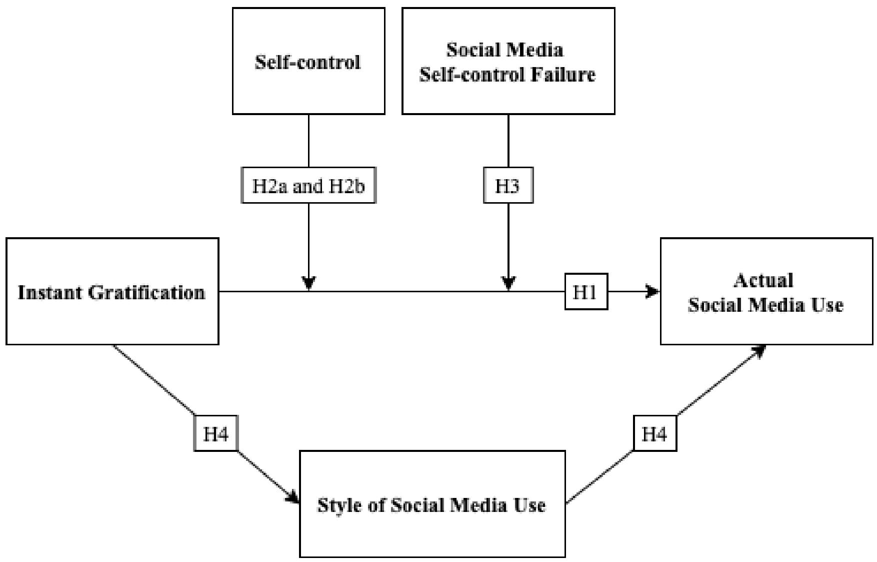
As noted above (see 'Reward learning' section), most of the SM events that are responsible for triggering neural responses on the brain's reward system, such as receiving Likes on one's own publications (Sherman et al., 2016), typically result of making active use of SMPs (e.g., posting one's own content). Rewarding the user (e.g., with Likes) mostly after (s)he had performed an active behavior (e.g., posting one's own content) — rather than after performing a behavior on the opposite of the continuum (e.g., scrolling through other's content) — can work as a positive reinforcement to not only keep users coming back but using SM in an active style. Lindström et al. (2021) observed a causal effect of received Likes on one's posts on one's frequency of engaging in active behaviors (i.e., posting). Therefore, if SMU is driven by rewards (Lindström et al., 2021), and rewards typically result from making active use of SM, people with a higher preference for instant gratification might get easily conditioned to adopt an active user profile in order to increase their rate of received rewards. Consequently, having an active style of social media use will likely lead to spending more time on SM, as it demands more attention from its users (e.g., to handle all push notifications reporting the received Likes). A recent study claimed that individuals who share content (be active users) on SMPs reported spending more time on SMPs, specifically on Facebook, compared to those who scroll through other's content (passive users) and give it a liking (Shaw et al., 2021). Thus, the following hypothesis is postulated:

> **H4:** The relationship between instant gratification and actual social media use is mediated by the style of social media use, such that lower (higher) levels of LDR Proportion lead to using social media more actively (more passively), which in turn lead to a heavier (lower) actual social media use (screen time and pickups).

Based on the hypotheses that are formulated above, a conceptual model is created. See Figure 1.

Figure 1.

A conceptual model based on the hypotheses formulated in this study. Self-reported and performance-based self-control and/or social media self-control failure moderate the relationship between instant gratification and actual social media use. Furthermore, style of social media use mediates this same relationship.



Method[1]

Design

To investigate to what extent there is a relationship between instant gratification and actual social media use, and whether this relationship is moderated by self-control (self-reported and performance-based) and social media self-control failure, and mediated by style of social media use, a cross-sectional survey research design was conducted, online, via Qualtrics software. The variables were the LDR proportion — participants' number of proportion of

[1] Materials, data, and the syntax file for analyses are available via the Open Science Framework at osf.io/546tg.

choices towards the larger, delayed rewards in the 27-item Monetary Choice Questionnaire (MCQ), and actual social media use, measured by the screen time (in minutes) and the number of pickups on five popular SMPs: Facebook, Twitter, Instagram, YouTube and TikTok (but see below). The moderator variables were participants' ability to self-control and to refrain from using SM. The former was assessed with both a performance-based (the refrain-from-blinking task) and a self-report measure (Brief Self Control Scale; BSCS) of self-control. The latter was measured with the social media self-control failure scale (SMSCF). Finally, we determined participants' style of social media use, measured with an adapted version of the Passive Active Social Media Use scale (PASMU-scale), to be explored as a mediator. The study was approved by the university's Research Ethics and Data Management Committee (#2021.25).

Participants

In total, 59 young adult participants completed the study survey. Participants were recruited both via the human subject pool (HSP) from Tilburg University (n = 30) and via convenience sampling (n = 29). Participants sampled via the HSP received one HSP course credit upon study completion. For convenience sampling, the study was promoted among prospective participants via WhatsApp and the SONA platform as "a scientific study on social media use" for which they would be "challenged to perform a refrain-from-blinking task". To be eligible to participate in this study, participants (1) had to be aged between 18 and 30 years old. The age restriction was set to this range to target young adults as, together with teenagers, they are in the age range that uses SM the most (*Social Media Fact Sheet*, 2019). Participants (2) were also required to use at least two of the five SM applications selected for the current study (Facebook, Instagram, Twitter, YouTube, and Tiktok). Finally, participants (3) had to own an iPhone with iOS 12 or above, and (4) be willing to record a video of themselves trying to blink as little as they can for a short period. Participants were asked to answer the survey on a laptop or a desktop computer, in a quiet room. Ten participants were excluded from the sample because they did not donate their social media screen times and the number of pickups (n = 4), did not provide their behavioral SMU data nor performed the refrain from blinking task (n = 3), participated two times in the study (n = 1), demonstrated straight-lining (n = 1), or were an extreme outlier (n = 1). Thus, the final sample used for the data analysis consisted of 49 participants (29 females) with a mean age of 22 years old (SD = 3.15); 28 participants were from HSP and 21 from convenience sampling.

Materials and Measures

Demographics. Participants were asked to answer two demographic questions. These questions concerned participants' gender (i.e., "What is your gender?") and age (i.e., "Please type in your age"). Possible answers to the gender question were "male", "female", "other", and "prefer not to say".

Instant Gratification (i.e., LDR Proportion). Participants' relative preference for a smaller instant reward instead of a larger delayed reward was assessed with the 27-item Monetary-Choice Questionnaire (MCQ; (Kirby et al., 1999). Participants were presented with a total of twenty-seven hypothetical scenarios for which they had to state their preference between a smaller, instant reward (e.g., €14 today) or a larger, delayed reward (e.g., €85 in 157 days). Research has shown that using hypothetical rather than actual rewards does not make a significant difference (Madden et al., 2003, 2004). All 27 items can be found in Appendix A. The proportion of choices towards the larger, delayed reward (i.e., *LDR Proportion*) was used as a measure of instant gratification. The lower the LDR Proportion, the higher the participant's tendency to choose instant rewards over larger delayed ones. Participants' choices to the MCQ were processed using an Excel-based spreadsheet tool that automatically scores and analyzes their choices (Kaplan et al., 2014). This tool provides the LDR Proportion for each participant, the natural logarithm of the discount parameter k (*In Overall k*), and the overall consistency (in percentage) of participants' responses. The LDR Proportion was highly correlated in the current study with the In Overall k, r (47) = -.97, $p < .001$, suggesting that the LDR Proportion is a valid measure to assess participant's preference for instant gratification (Myerson et al., 2014). Also, all the participants ($N = 49$) scored above 75% in '*Overall Consistency*', suggesting reliable responses, such that all participants were included in the LDR Proportion analyses (Kaplan et al., 2014).

Self-reported Self-control (i.e., BSCS). To assess participant's general ability to inhibit impulses, urges, and dominant responses, both a self-report (i.e., Brief Self-Control Scale, BSCS; Tangney et al., 2004) and a performance-based measure (i.e., the refrain-from-blinking task) of self-control were administered. The 13-item BSCS (Tangney et al., 2004) is a well-established self-report measure of trait self-control. Example items are: "I am lazy" and "I say inappropriate things". Items are rated on a 5-point scale, ranging from 1 (not at all like me) to 5 (very much like me). All 13-items can be found in Appendix C. The possible range of scores is 13 to 65, created by summing up all the item scores. A higher score indicates higher self-reported self-control. The reliability of this scale was acceptable (Cronbach's $\alpha = .71$).

Performance-based Self-control (i.e., Blink Rate). As a performance-based measure of self-control, we employed the refrain-from-blinking task as an objective measure of participants' capacity to inhibit a dominant response, i.e., blinking the eyes. This measure was inspired by

Schmeichel and Zell's study (2007), who found higher scores on self-reported self-control (i.e., BSCS) to be a predictor of fewer eye blinks on the refrain-from-blinking task (while controlling for participant's arousal; Schmeichel & Zell, 2007). However, in the current study, due to COVID-19 restrictions, the refrain-from-blinking task was not employed in the lab, as in Schmeichel & Zell's study (2007). Instead, in the current online study, the measure was self-employed by the participants from home. Participants were instructed to look straight into their smartphone's front camera while they recorded themselves trying to blink as little as they could for a 2-minute period (see instructional video on osf.io/546tg). The recordings were later assessed by the researcher (JR), who manually counted the number of participants' eye blinks (i.e., Blink Rate) produced within the two minutes. The coding followed the Schmeichel & Zell's criteria (2007) shared by personal communication via email: "We counted all full blinks, even if they occurred very shortly after another blink". A higher Blink Rate indicates lower performance-based self-control. To test for inter-rater reliability, ten videos were randomly selected from the sample and assigned to a second-rater that was blind to study hypotheses. The counts of the two raters were highly correlated (r = .98). Hence, the counting of the first rater was used in the analyses. Furthermore, participants were asked if they were using contact lenses during the refrain-from-blinking task, as it might have an impact on Blink Rate. Only four participants reported using contact lenses, with two participants scoring below the overall sample Blink Rate mean (M = 11.24, SD = 8.59). Participants using contact lenses were included in the data analyses.

Tense-arousal. Similar to Schmeichel and Zell's study (2007), the Tense-arousal subscale of the UWIST Mood Adjective Check List (Matthews et al., 1990) was used to control for participants' level of arousal, which has been claimed to affect their performance on the behavioral measure of self-control (Schmeichel & Zell, 2007). Right before performing the refrain from blinking task, participants were asked: "How accurately do the following adjectives describe how you are feeling at this moment?". Scale items include "composed", "anxious", "jittery", "calm", "tense", "passive", and "relaxed", rated from 1 (not accurately at all) to 5 (extremely accurately). All the low arousal items (i.e., composed, calm, passive, and relaxed) were reverse-scored. The possible range of scores was 7 to 35, created by summing up all the item scores. The reliability of this scale was not acceptable (Cronbach's $\alpha = .33$), nor was it possible to increase reliability by deleting one or more items. This lower reliability score might be due to participants' difficulties interpreting the meaning of some adjectives, such as "jittery" or "composed". Therefore, we did not control for participants' tense arousal in the data analyses, which will be discussed later as a limitation of the current study.

Social Media Self-control Failure (i.e., SMSCF). To assess how often participants cease to resist using SM apps, even though it might compromise their long-term goals or ongoing tasks at that moment, the Du and Kerkhof 's three-item Social Media Self-control Failure scale (2018) was used. Items are: (1) "How often do you give in to a desire to use social media even though your social media use at that particular moment conflicts with other goals (for example: doing things for school/study/work or other tasks)?", (2) "How often do you give in to a desire to use social media even though your social media use at that particular moment makes you use your time less efficiently?", (3) "How often do you give in to a desire to use social media even though your social media use at that particular moment makes you delay other things you want or need to do?". Items are rated on a 5-point scale, ranging from 1 (almost never) to 5 (very often). Participants' SMSCF score was calculated by averaging across the three items. A higher score indicates less self-reported self-control to resist using SM platforms. The reliability of this scale was very good (Cronbach's α = .88).

Style of Social Media Use. To assess participants' style of social media use, in a continuum from passive to active use, they were asked to indicate how often they typically engage in a series of six behaviors (three for passive and three for active behaviors) while using SM platforms. An adapted version of Escobar-Viera, et al.'s Passive and Active Social Media Use scale (PASMU-scale) (2018) was used. The first item of the original scale (i.e., "Read discussions"; Escobar-Viera et al., 2018), was replaced by the "Scroll through the newsfeed" item from Hanley et al.'s Passive and Active Usage Scale (2019). In our view, "Read discussions" has a strong overlap with the second item of the PASMU-scale, "Read comments/reviews". In contrast, the action of scrolling through the newsfeed, which was not present in the original PASMU-scale, might be one of the most common behaviors of passive users (Hanley et al., 2019). An example item of active behavior in the PASMU-scale is "Watch videos or view pictures". Items are rated on a 6-point scale, ranging from 1 (never) to 6 (several times a day). All six items can be found in Table 2, Appendix D. The first three items are relative to passive use, and the other three are relative to active use. The averages across the three items resulted in passive and active social media use scores. To calculate a continuous variable from passive to active usage, each participant's passive usage average score was subtracted from the active usage average score. This resulted in an overall score for style of social media use ranging from -5 to 5, with higher scores indicating active usage. Furthermore, participants were asked to answer one (isolated) question concerning their style of social media use (i.e., "How often do you typically put likes on posts/pictures/videos while using social media?"). This question was also inspired by Escobar-Viera et al. 's study (2018), who did not include the 'liking' item on the final scale because it fits neither the passive nor the active sub-scale. In the current study, the 'liking' item was only assessed to provide insights on the characteristics of the sampled population in regards to what is one of the most typical behaviors of social media users (i.e. liking; Escobar-Viera et al., 2018).

Actual Social Media Use (i.e., Instagram screen time and pickups). To assess participants' actual social media use, we focused on Facebook, Instagram, YouTube, Twitter, and TikTok use because these are the main SM apps currently in use (de Best, 2019). Participants were asked to donate their behavioral SMU data (screen time and the number of pickups) registered via the Screen Time app. This is a built-in iOS app that automatically logs data usage of every application with which the user has interacted on the iPhone (iOS 12 or above). As the Screen Time app displays the screen time values and the number of pickups for each app in the form of the total Sum minutes per week, participants were asked to report their data regarding the past week to the day of data collection. This way, we guaranteed that for all the participants, the daily average screen time values and pickups were determined based on seven days of smartphone usage. In addition, participants were also asked to provide screenshots of the Screen Time app screens with their behavioral SMU data, either via WhatsApp or email. See Figure 1, in Appendix B. This was important to ensure that the data was complete and accurate. Note that if for any reason, participants did not use the smartphone on any day of the past week to the day of data collection, they were asked to report their data in regards to a previous week — on which they did a full use of the smartphone (seven days). This was the case for two participants.

Facebook, Instagram, Twitter, YouTube, and TikTok were chosen to assess participants' actual social media use (screen time and pickups) because these are among the most popular SM apps (de Best, 2019). Facebook, Instagram, Twitter, and YouTube were also categorized as SM apps by Schulz van Endert and Mohr (2020). They found social media screen time to be a significant predictor of users' preference for larger, delayed rewards. However, note that despite our attempt to collect data for all the five SM apps, only the applications used by all the participants of the final sample were analyzed (i.e., Instagram). This allowed for meaningful analyses that could be performed on a significant part of the sample, as the targeted sample (i.e., 60 participants) was already small due to time constraints.

Furthermore, to check participants' reliance on using SM apps in the smartphone to access SM platforms, participants were asked: "Which device do you use the most to access social media platforms". To access SM platforms, 45 participants reported to use the "smartphone", 4 participants reported to use "more or less equally divided across the smartphone and other devices", and none participant reported to use "other devices (e.g., desktop or tablet)". Further, they were asked: "Do you access your social media platforms typically via the app (e.g., the Instagram app) or via the website (e.g., instagram.com) on the smartphone?". To access SM platforms on the smartphone, 47 participants reported to do it "typically via the application", 1 participant reported to do it "typically via the website", and 1 participant reported to do it "typically more or less equally divided across the app and the website". To have more contextual information on participants' SMU, they were also asked: "How long ago (in years) did you create your first social media account?" (M = 9.88, SD = 2.75) and "Do you use social media apps in your smartphone for any other purpose than personal use?". Only nine participants reported using SM apps on their smartphone to "manage the social media accounts from a company or an organization". In comparison, 40 participants reported to use SM apps on their smartphones exclusively "for personal use". As can be inferred by the data, assessing participants' actual social media use via the use of SM applications logged in on their smartphones accurately represents their actual use of SMPs. However, conclusions on the findings in the relationship between instant gratification (i.e., LDR Proportion) and actual social media use (i.e., Instagram screen time and pickups) should consider that nine participants spent extra time on SM due to work-related obligations. This will be discussed later among other limitations related to assessment of participants' actual social media use.

Procedure

Due to COVID-19 restrictions, this study was performed entirely online via Qualtrics software. Participants were informed about the eligibility criteria (see the section on 'Participants' above) and that they were about to participate in "a scientific study on social media use", for which they provided their informed consent. See recruitment materials and study information sheet on osf.io/546tg. The study took approximately 35 minutes to complete. Firstly, participants were asked for demographic information (gender and age). Then, as participants were still fresh and enthusiastic (we assumed), they were instructed to perform the (quite demanding) refrain-from-blinking task, which preceded the TA scale. Before performing the task, participants watched an instructional video on how to self-employ and record the refrain-from-blinking task. The video can be watched on osf.io/546tg. We tried to replicate the original setting used in the lab by Schmeichel and Zell (2007) but in an online and self-employed format. In short, participants were instructed to look straight into their smartphone's front camera while they record themselves trying to blink as least as they can for two minutes. The moment to start and finish trying to refrain from blinking and stop the recording was signalized by an alarm sound displayed in the .mp3 file (see osf.io/546tg), which participants had played in the Qualtrics survey right after watching the instructional video. At the end of the task, they were asked to share the recording with the researcher (JR) via WhatsApp or email. Next, the self-report questionnaires were administered in the following order: the 27-item MCQ, the 13-item BSCS, the SMSCF-scale, and the adapted version of the PASMU-scale. Then, participants answered four multiple-choice questions that assessed their social media-related habits, and were asked to manually report their behavioral SMU data (screen time and the number of pickups, as registered via the native Screen Time app) and to share the respective screenshots via WhatsApp or email. Participants' behavioral SMU data (screen time and pickups) were assessed at the end of the survey to avoid any priming effect on the self-report questionnaires. We believe that participants were (negatively) surprised, at the end of the survey, when asked to be so objective in their reporting on SMU; however, this might have prevented sample bias. As relying upon individuals' willingness to donate their SMU data raises concerns about sampling bias (Shaw et al., 2021). Even though participation was entirely voluntary and participants could still drop out at the end of the survey. However, none out of 59 participants refused to report their SMU data at the end of the survey. Only four participants did not provide their SMU data after completing all the previous questions, and that was because the Screen Time app was turned off on their smartphone and did not track their activity. As noted above (in the 'Participants' section), the data from these four participants were deleted from the analyses. Finally, all participants were debriefed via WhatsApp or email that we were "looking for relationships between actual social media use, instant gratification, and self-control". Note that all data was treated and stored fully anonymously. Participants' recordings and screenshots were deleted immediately after coding them.

Data-analyses

To allow for meaningful analyses that could be performed on a significant part of the final sample, only the SM apps that were used by all the participants were included in the data analyses that included the variable actual social media use. In the current sample ($N = 49$), at the time of data collection, 49 participants reported to use Instagram, 32 participants reported to use Facebook, 25 participants reported to use TikTok, 25 participants reported to use YouTube, and 12 participants reported to use Twitter. Therefore, only the SM app Instagram was used to create the actual social media use (screen time and pickups) scores.

All data analyses were performed using SPSS. To test the first core hypothesis that there is a positive correlation between instant gratification (i.e., LDR Proportion) and actual social media use (i.e., Instagram screen time and pickups), a Pearson's correlation test was performed to explore the expected negative correlation between the LDR Proportion and Instagram screen time and pickups (H1). Next, the moderating effects of self-reported self-control (i.e., BSCS scores; H2a), performance-based self-control (i.e., Blink Rate; H2b), and social media self-control failure (i.e., SMSCF scores; H3) on the relationship between instant gratification (i.e., LDR Proportion) and actual social media use (i.e., Instagram screen time and pickups) were tested using Hayes' PROCESS macro, model 1 (2017). The predictor variables were mean-centered to minimize multicollinearity. Finally, the mediating effect of style of social media use on the relationship between instant gratification (i.e., LDR proportion) and actual social media use (i.e., Instagram screen time and pickups) (H4) was tested using Hayes' PROCESS macro, model 4 (2017). PROCESS is an add-on to SPSS that allows statistical mediation and moderation analyses to be integrated with a series of models (Hayes, 2017). Additionally, with Pearson's correlations, we tested a set of sanity-check hypotheses:

SH1: There is a positive correlation between self-reported and performance-based self-control, which will show as a negative correlation between the BSCS scores and the Blink Rate.

SH2: There is a positive correlation between self-reported self-control and social media self-control failure, which will show as a negative correlation between the BSCS scores and the SMSCF scores.

SH3: There is a positive correlation between social media self-control failure and performance-based self-control, which will show as a positive correlation between the SMSCF scores and the Blink Rate.

Results

Overall Correlations and Tests of the Sanity-check Hypotheses

On average, participants scored 37.50 on BSCS (i.e., self-reported self-control; *SD* = 5.90), produced an average Blink Rate of 12 blinks within the 2-minutes refrain-from-blinking task (i.e., performance-based self-control; *SD* = 11.59), and scored 3.75 on SMSCF (*SD* = 0.88). While the data on the BSCS and the SMSCF was normally distributed (BSCS: $\text{z-score}_{\text{skewness}}$ = 0.22, $\text{z-score}_{\text{kurtosis}}$ = -0.24, and SMSCF: $\text{z-score}_{\text{skewness}}$ = -1.79, $\text{z-score}_{\text{kurtosis}}$ = 0.18), the data on the Blink Rate was not normally distributed ($\text{z-score}_{\text{skewness}}$ = 7.27, $\text{z-score}_{\text{kurtosis}}$ = 14.01). There was an extreme outlier with a score of 67. Removing the outlier improved the data on the

Blink Rate considerably (z-score$_{skewness}$ = 2.68, z-score$_{kurtosis}$ = 1.36), even though it still shows a slightly high skewness.

SH1: A Person's correlation was conducted to test whether previous findings on the relationship between self-reported self-control (i.e., BSCS scores) and performance-based self-control (i.e., Blink Rate) replicate. As the data on the Blink Rate had a slightly high skewness value (z-score$_{skewness}$ = 2.68, z-score$_{kurtosis}$ = 1.36), we also provide the bootstrapped 95% confidence intervals. The analysis showed no significant relationship between participants' BSCS scores and their Blink Rate, $r(47) = .14$, $p = .346$, 95% CI [-.15,.46]. Thus, we did not replicate previous findings (Schmeichel & Zell, 2007) and did not confirm our sanity-check hypothesis that there is a positive correlation between the self-reported and performance-based self-control, which will show as a negative correlation between the BSCS scores and the Blink Rate (SH1); indeed, the correlation was in the opposite direction.

SH2: A Pearson correlation was conducted to test whether previous findings on the relationship between self-reported self-control (i.e., BSCS scores) and social media self-control failure (i.e., SMSCF scores) replicate. The analysis showed that participants who have a lower score on the BSCS are significantly more likely to have a higher score on the SMSCF, $r(47) = -.56$, $p < .001$. 31.36% of the variance in BSCS scores (i.e., self-reported self-control) was accounted for by participants' SMSCF scores (i.e., difficulty to refrain from using social media). Thus, we replicated previous findings (Du et al., 2018) and confirmed the sanity-check hypothesis that there is a positive correlation between self-reported self-control and social media self-control failure, which will show as a negative correlation between the BSCS scores and the SMSCF scores (SH2).

SH3: A Person's correlation was conducted between social media self-control failure (i.e., SMSCF scores) and performance-based self-control (i.e., Blink Rate). As the data on the Blink Rate had a slightly high skewness value ($z\text{-score}_{skewness} = 2.68$, $z\text{-score}_{kurtosis} = 1.36$), we also provide the bootstrapped 95% confidence intervals. The analysis showed no significant relationship between participants' SMSCF scores and their Blink Rate, $r(47) = -.20$, $p = .169$, 95% CI [-.15,.46]. Thus, we did not confirm our sanity-check hypothesis that there is a positive correlation between social media self-control failure and performance-based self-control, which will show as a positive correlation between the SMSCF scores and the Blink Rate (SH3); indeed, the correlation was in the opposite direction.

Overall Correlations: Below, in Table 1, we provide the correlation coefficients and corresponding *p*-values across all the variables. In addition to the sanity-check hypotheses mentioned above, there were some other potentially interesting, but exploratory, correlational findings that we briefly address here. Firstly, there was a positive correlation between daily average Instagram screen time and the daily average number of Instagram pickups, $r(47) = .45$, $p = .001$. The analysis showed that the more social media users open the Instagram app (i.e., pickups), the higher is their screen time spent on the app. This makes intuitive sense and shows the validity of the measures taken to assess participants' Instagram actual use. Similarly, the analysis showed that the higher is the daily average screen time spent on Instagram, the higher is the daily average screen time spent on the 'Social' category, $r(47) = .41$, $p = .004$. Social screen time is an iOS predefined category representing the total screen time spent on all SM and messaging platforms (e.g., WhatsApp) with which the user has interacted with. See Appendix B. Also, the higher is the participants' daily average number of Instagram pickups, the higher is their daily average number of smartphone pickups, $r(47) = .44$, $p = .002$. Another foreseeable result was that the older the participants are, the more years they have spent using SM (i.e., Instagram), $r(47) = .71$, $p < .001$. Finally, it seems that younger people have higher (perceived) difficulty to refrain from using social media when its usage conflicts with their long-term goals or ongoing tasks at that moment, $r(47) = -.29$, $p = .047$.

'Liking' Item: Among the 49 participants, 35 participants reported that they typically put likes on posts/pictures/videos on SM "several times a day", 5 participants reported to do it "once a day", 6 participants reported to do it "2-6 times a week", 1 participant reported to do it "once a week", and finally 2 participants reported to do it "less than once a week".

Table 1.

Scale, means, standard deviations, and correlations across all the variables. Correlation coefficients are reported above the table diagonal, whereas corresponding p-values are reported below the table diagonal.

	Scale	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Instagram screen time	Daily average in minutes	64.06	38.90	--	.45** [.266, .658]	.41** [.156, .608]	.17	-.02	.28* [.040, .489]	-.29* [-.496, -.051]	.07	-.04	-.12	-.09	.13	.10
2. Instagram pickups	Daily average number	14.99	13.90	.001	--	.26	-.08	.44** [.258, .611]	-.00	-.07	-.02	.01	-.06	-.05	.11	.19
3. Social screen time	Daily average in minutes	162.71	66.85	.004	.077	--	.59*** [.343, .768]	.34* [.039, .637]	-.09	.17	-.09	.19	.07	.00	-.03	.02
4. Smartphone screen time	Daily average in minutes	332.71	116.30	.251	.598	< .001	--	-.01	-.09	.12	-.06	.30* [.000, .564]	-.06	-.09	-.12	-.19
5. Smartphone pickups	Daily average number	130.04	53.31	.897	.002	.016	.941	--	-.16	.15	.04	.11	.04	.08	-.19	.09
6. LDR Proportion	0 - 100%	44.82	14.09	.049	.980	.533	.556	.269	--	-.97*** [-.981, -.938]	.07	-.01	.11	-.05	-.21	-.16
7. ln overall k	-10 - 0	-4.65	1.19	.045	.631	.232	.408	.295	< .001	--	-.01	.07	-.08	.07	.15	.10
8. BSCS (i.e., self-reported self-control)	13 - 65	37.51	5.97	.627	.909	.522	.669	.804	.623	.952	--	.14	-.55*** [-.733, -.332]	.15	-.01	-.10
9. Blink Rate (i.e., performance-based self-control)	Blinks in two minutes period	11.24	8.59	.811	.936	.192	.036	.449	.961	.615	.346	--	-.20	.09	-.08	-.20
10. SMSCF	1 - 5	3.75	.89	.411	.665	.653	.705	.804	.434	.609	< .001	.169	--	-.06	-.29* [-.518, -.017]	-.17
11. Style of social media use	-5 - 5	-2.34	1.30	.536	.735	.999	.557	.597	.758	.655	.318	.537	.688	--	.03	-.01
12. Age	In years	22.02	3.15	.389	.463	.846	.399	.195	.139	.293	.943	.579	.047	.863	--	.71*** [.048, .565]
13. Years of SMU	In years	9.89	2.75	.492	.203	.889	.182	.523	.260	.495	.516	.179	.231	.971	< .001	--

Note: $N = 49$. * indicates $p < .05$. ** indicates $p < .01$. *** indicates $p < .001$.

Core hypotheses [2]

H1: There is a positive correlation between instant gratification and actual social media use, which will show as a negative correlation between the LDR Proportion and actual social media use (i.e., Instagram screen time and pickups).

Participants, on average, spent 64.06 minutes per day on Instagram (SD = 38.90) and opened the application on average 15 times per day (i.e., pickups; SD = 13.90). They, on average, opted for the larger delayed reward over the smaller near-term reward (i.e., LDR Proportion) in 44.82% of the choices (SD = 14.09). To test the first core hypothesis (H1), two separate Pearson's correlations were conducted: one for Instagram pickups and one for Instagram screen time. While the data on LDR proportion was normally distributed (z-score$_{skewness}$ = 0.04, z-score$_{kurtosis}$ = 0.25), the data on Instagram pickups was not normally distributed (z-score$_{skewness}$ = 5.02, z-score$_{kurtosis}$ = 4.08). Therefore, we also provide the bootstrapped 95% confidence intervals. The analysis showed no significant relationship between these two variables, $r(47) = -.01$, $p = .980$, 95% CI [-.25,.27]. Instagram screen time data was normally distributed (z-score$_{skewness}$ = 1.95, z-score$_{kurtosis}$ = -0.22), and the analysis showed that participants with a higher preference for a smaller near-term reward over a larger delayed reward, are significantly more likely to spend *less* time on Instagram $r(47) = .28$, $p = .049$. 8.01% of the variance in Instagram screen time was accounted for by participants' proportion of choices towards the larger delayed reward (i.e., LDR Proportion). Overall, we rejected hypothesis 1 that there is a positive correlation between instant gratification and actual social media use (screen

[2] Hypotheses were aimed at both screen time and number of pickups as dependent variables. However, for the moderation (H2a, H2b and H3) and mediation analyses (H4) we observed for Instagram pickups systematically the same outcomes as for Instagram screen time as the dependent variable (i.e., no significant effects). For the sake of brevity, we only report on the latter dependent variable.

time and pickups), which would have shown as a negative correlation between the LDR Proportion and actual social media use (i.e., Instagram screen time and pickups).

H2a: The relationship between instant gratification and actual social media use is stronger for users with low than high self-reported self-control.

To test hypothesis 2a, a moderation analysis was conducted with LDR Proportion as the predictor variable, Instagram screen time as the outcome variable, and BSCS (i.e., self-reported self-control) as the moderator of the relationship between LDR Proportion and Instagram screen time. Before running the analysis, the assumptions needed to be checked. The assumptions' testing showed that there were two people (4%) with a standardized residual larger than two, so outliers are not a problem here. The assumption of multicollinearity was met by centering predictor variables on the mean. There were two cases with a worrisome Cook's distance (i.e., .106 and .118), one case with a considerable Mahalanobis distance (i.e., 17.829) and a centered leverage value larger than three times the average leverage score (i.e., .371), and another case with a leverage value larger than three times the average leverage score (i.e., .281). However, the standardized DFBetar(s) with absolute values were not above 1, which indicates that these four cases have little influence on the model parameters. Thus, they were included in the analysis. All the remaining assumptions were met (independence of errors, normality of the residuals, heteroscedasticity, and linearity).

The actual analysis demonstrated that the model with LDR Proportion, BSCS (i.e., self-reported self-control), and the interaction between LDR Proportion and BSCS to predict Instagram screen time was not significant, $R^2 = .13$, $F(3, 45) = 2.27$, $p = .094$. Likewise, there was no significant main effect of LDR Proportion on Instagram screen time, $b = 0.62$, $SE = 0.40$,

p = .12, 95% BCI [-0.17, 1.42]. There was also no significant main effect of BSCS on Instagram screen time, b = 0.65, SE = 0.93, p = .49, 95% BCI [-1.22, 2.52]. In addition, there was no significant interaction effect between LDR Proportion and BSCS on Instagram screen time, b = 0.09, SE = 0.06, p = .12, 95% BCI [-0.03, 0.21]. Overall, we can conclude that our data does not support the hypothesis that the relationship between instant gratification and actual social media use (i.e., Instagram screen time) is stronger for users with low than high self-reported self-control (H2a).

H2b: The relationship between instant gratification and actual social media use is stronger for users with high than low performance-based self-control.

To test hypothesis 2b, a moderation analysis was conducted with LDR Proportion as the predictor variable, Instagram screen time as the outcome variable, and Blink Rate (i.e., performance-based self-control) as the moderator of the relationship between LDR Proportion and Instagram screen time. The assumptions' testing showed that there were two people (4%) with a standardized residual larger than two, so outliers are not a problem here. The assumption of multicollinearity was met by centering predictor variables on the mean. There were two cases with a worrisome Cook's distance (i.e., .109 and .195), and two cases with a considerable Mahalanobis distance (i.e., 15.104 and 16.094) and a centered leverage value larger than three times the average leverage score (i.e., .314 and .335 respectively). However, the standardized DFBetar(s) with absolute values were not above 1, which indicates that these four cases have little influence on the model parameters. Thus, they were included in the analysis. All the remaining assumptions were met (independence of errors, normality of the residuals, heteroscedasticity, and linearity).

The analysis demonstrated that the model with LDR Proportion, Blink Rate (i.e., performance-based self-control), and the interaction between LDR Proportion and Blink Rate to predict Instagram screen time was not significant, $R^2 = .08$, $F(3, 45) = 1.33$, $p = .276$. Likewise, there was no significant main effect of LDR Proportion on Instagram screen time, $b = 0.78$, $SE = 0.40$, $p = .05$, 95% BCI [-0.01, 1.58]. There was also no significant main effect of Blink Rate on Instagram screen time, $b = -0.14$, $SE = 0.65$, $p = .84$, 95% BCI [-1.45, 1.18]. In addition, there was no significant interaction effect between LDR Proportion and Blink Rate on Instagram screen time, $b = 0.01$, $SE = 0.04$, $p = .89$, 95% BCI [-0.08, 0.09]. Thus, we reject the hypothesis that the relationship between instant gratification and actual social media use (i.e., Instagram screen time) is stronger for users with high than low performance-based self-control (H2b).

H3: The relationship between instant gratification and actual social media use is stronger for users with high than low social media self-control failure.

To test hypothesis 3, a moderation analysis was conducted with LDR Proportion as the predictor variable, Instagram screen time as the outcome variable, and SMSCF as the moderator of the relationship between LDR Proportion and Instagram screen time. The assumptions' testing showed that there were two people (4%) with a standardized residual larger than two, so outliers are not a problem here. The assumption of multicollinearity was met by centering predictor variables on the mean. There were three cases with a worrisome Cook's distance (i.e., .102, .225 and .299), and one case with a considerable Mahalanobis distance (i.e., 20.471) and a centered leverage value larger than three times the average leverage score (i.e., .427). However, the standardized DFBetar(s) with absolute values were not above 1, which indicates that these four cases have little influence on the model parameters. Thus, they were included in the analysis. All the remaining assumptions were met (independence of errors, normality of the residuals, heteroscedasticity, and linearity).

The analysis demonstrated that the model with LDR Proportion, SMSCF, and the interaction between LDR Proportion and SMSCF to predict Instagram screen time was not significant, $R^2 = .15$, $F(3, 45) = 2.67$, $p = .058$. Likewise, there was no significant main effect of LDR Proportion on Instagram screen time, $b = 0.64$, $SE = 0.40$, $p = .12$, 95% BCI [-0.17, 1.46]. There was also no significant main effect of SMSCF on Instagram screen time, $b = -8.14$, $SE = 6.10$, $p = .19$, 95% BCI [-20.40, 4.16]. In addition, there was no significant interaction effect between LDR Proportion and SMSCF on Instagram screen time, $b = -0.68$, $SE = 0.43$, $p = .12$, 95% BCI [-1.55, 0.18]. Thus, we reject the hypothesis that the relationship between instant gratification and actual social media use (i.e., Instagram screen time) is stronger for users with high than low social media self-control failure (H3).

H4: The relationship between instant gratification and actual social media use is mediated by the style of social media use, such that lower (higher) levels of LDR Proportion lead to using social media more actively (more passively), which in turn lead to a heavier (lower) actual social media use (screen time and pickups).

To test our hypothesis 4, a mediation analysis was conducted. LDR Proportion was set as the independent variable, actual social media use (i.e., Instagram screen time) as the dependent variable, and style of social media use as the mediator. On average, participants scored -2.32 on style of social media use ($SD = 1.30$) on a range from -5 to 5. As can be seen by the data, there was not much variance in participants' style of social media use. Only 1 out of 49 participants scored above 0 (i.e., 2.33), which indicates that this participant self-reported behaving as an active user when using SM. So, most of our sampled users perceived their usage of SM to be typically passive. The analysis showed that there was no significant effect of LDR Proportion and style of social media use (b = -.00, SE = .01, p = .758), and there was no significant effect of style of social media use and Instagram screen time (b = -2.33, SE = 4.21, p = .583). Therefore, we reject the hypothesis that the relationship between instant gratification and actual social media use is mediated by the style of social media use, such that lower (higher) levels of LDR Proportion lead to using SM more actively (more passively), which in turn lead to a heavier (lower) actual social media use (screen time and pickups) (H4). However, results on mediation effects should be interpreted with caution as the sampled population was not varied on style of social media use (floor effects).

Discussion

The current study investigated the relationship between instant gratification and actual social media use, and whether this relationship is moderated by users' self-reported and performance-based self-control and/or ability to refrain from using social media when its use conflicts with other goals. In addition, we explored whether a user's style of social media use mediates the relationship between instant gratification and actual social media use. Note that, despite our attempt to collect participants' actual social media use data for all the five SM apps of interest in the current study (i.e., Facebook, Instagram, Twitter, YouTube, and TikTok), only Instagram was used by all the participants of the final sample (N = 49). That is why only behavioral data on Instagram actual use (screen time and pickups) was included in the data analyses that included the variable actual social media use. We will get back to this in the

'Limitations and Recommendations for Future Research' section. Contrary to the core hypotheses, there was no significant positive correlation between instant gratification and actual social media use (H1); the above relationship was not moderated by self-reported self-control (H2a), performance-based self-control (H2b), or social media self-control failure (H3); and there was no mediating effect of style of social media use in the relationship between instant gratification and actual social media use (H4). In regards to the sanity-check hypotheses, there was a positive correlation between self-reported self-control and social media self-control failure (SH1); however, there was no significant correlation between self-reported self-control and performance-based self-control (SH2); and there was no significant correlation between social media self-control failure and performance-based self-control (SH3). All the findings are elaborated on below.

The Relationship Between Instant Gratification and Actual Social Media Use

We observed a significant relationship between instant gratification and time spent on Instagram. However, the direction of the effect was opposite to what was expected, as we expected a positive correlation between instant gratification and actual social media use (H1). Specifically, participants who had a higher need for instant gratification (i.e., a preference for a smaller near-term reward over a larger delayed reward) were significantly more likely to spend *less* time on Instagram. This finding is inconsistent with previous work. For example, Schulz van Endert and Mohr (2020) found higher screen time spent on SM to be a positive predictor of participants' choices towards the larger, delayed reward. Moreover, various studies found higher technology use to be associated with higher preference for instant gratification (Delaney et al., 2018; Frost et al., 2019; Hadar et al., 2017; Tang et al., 2017; Wilmer et al., 2019; Wilmer & Chein, 2016).

The unexpected negative relationship between instant gratification and Instagram screen time may relate to the fact that our sample of participants mainly included relatively passive users of SM. This means that participants of the current study self-reported to have a higher tendency to perform passive behaviors (e.g., scrolling through the newsfeed) than to perform active behaviors (e.g., posting one's content) when spending time on SM in general. Almost all participants (n = 48) self-reported to be primarily passive users of SM, aligning with previous findings (e.g., Shaw et al., 2021). It seems that the passive style is the norm of SMU lately, but some users are more active than others (Shaw et al., 2021). On reflection, performing this kind of behavior (i.e., passive style of social media use) may have had implications on the type and intensity of rewards experienced by participants when spending time on Instagram. As exposed above in the 'Theoretical Framework' section, receiving rewards on SM (e.g., receiving Likes on one's post; which is responsible for activating the brain's reward processing system (Sherman et al., 2016)) is often the result of an active behavior (e.g., posting). Also, engagement with an Instagram-like platform with the expectation of being rewarded was previously found to be reflected in an activity associated with active style of social media use (i.e., posting; Lindström et al., 2021). Therefore, as the sampled population perceived themselves as passive users of SM, we can assume that participants of the current study did not have much of an intensely rewarding experience when using Instagram. Therefore, it is likely that their engagement with SM was not driven by rewards seeking but by any other possible purpose. For example, to alleviate boredom (Fullwood et al., 2017). Nonetheless, among the sampled population, which is primarily passive users of SM, there were still differences in their preference for instant gratification, which were *negatively* associated with Instagram screen time. So, it is reasonable to expect passive users of SM with a higher preference for instant gratification to spend less time on Instagram: As Instagram is not a primary source of instant rewards, they tend to leave more quickly to spend time on other places that may actually provide participants with an instantly rewarding experience (e.g., gaming online, Schulz van Endert & Mohr, 2020; offline social interactions, Meshi et al., 2015).

The participants' data on overall smartphone screen time presented in participants' screenshots, see Appendix B, offered an interesting opportunity to perform exploratory tests on the question about whether passive social media users' preference for instant gratification correlates positively with time spent on other apps than Instagram. If our reasoning above is correct, we would expect negative correlations between LDR Proportion and time spent on other apps in the smartphone (i.e., calculated as follows: the 'daily average smartphone screen time' minus the 'daily average Instagram screen time'). Indeed, the exploratory analyses on the current data showed that LDR proportion — the proportion of choices towards the larger, delayed reward, which was used as a measure of instant gratification — negatively correlates (though not significantly) with time spent on other apps that are not Instagram.[3] In other words, passive social media users with a higher preference for instant gratification may be more likely to briefly check but then leave Instagram (as it is not a primary source of instant rewards) than self-reported passive social media users with a lower preference for instant gratification: a higher need for instant gratification represents a larger 'pull' by other, more rewarding environments.

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[3] A Pearson's correlation was conducted between LDR Proportion and 'smartphone overall screen time minus Instagram screen time' among the participants who scored below 0 in style of social media use i.e., passive use (N = 48). The participant who scored 2.33 in the style of social media use was excluded from the sample as she represented an active user of SM. The analysis showed no significant correlation between LDR Proportion and 'smartphone overall screen time minus Instagram screen time'. However, the direction of the effect was in the expected direction, $r(46) = -.16$, $p = .275$.

The corresponding correlations were not significant, but this may present inspiration for future and more dedicated research on this issue.

Moderation by Self-control

The current study showed no significant moderation of the relationship between instant gratification and actual social media use, by the various self-control measures (i.e., self-reported self-control, H2a; performance-based self-control, H2b; and social media self-control failure, H3). These findings are, on the one hand, (indirectly) inconsistent with previous findings by Wilmer & Chein (2016), who showed that individual differences in participant's ability to self-control (assessed behaviorally and through self-report) mediates the relationship between instant gratification and (self-reported) smartphone usage. Even though there have been claimed concerns about the validity of self-report measures of technology engagement (Parry et al., 2020). On the other hand, the present findings concur with Wilmer et al. (2019) and Schulz van Endert and Mohr's (2020) subsequent studies, which found no significant moderating effect of self-control in the relationship between instant gratification and media engagement (assessed objectively).

In part, findings of the current study may be explained by the lack of a significant positive correlation between instant gratification and actual social media use (H1) to begin with. This counters the theoretical basis from which we expected the moderation by self-control. In addition, the sample size in the current study (i.e., 49 participants) may not have been adequate to detect potentially existing moderation effects. A previous study that explored the role of participants' ability to self-control in the relationship between instant gratification and technology engagement included 91 participants in the analyses (Wilmer & Chein, 2016).

Furthermore, there were some limitations with the assessment of performance-based self-control through the online version of the refrain-from-blinking task that may have decreased the reliability of the scores. This will be elaborated in the 'Limitations and Recommendations for Future Research' section. Future research should further explore the role of self-control in the relationship between instant gratification and actual social media use within a larger sample size to increase statistical power, and employ an in-lab assessment of performance-based self-control — as elaborated further in the 'Limitations and Recommendations for Future Research' section.

Mediation by Style of Social Media Use

No significant mediating effect of style of social media use was found on the relationship between instant gratification and actual social media use. So, no support was found for the fourth, last hypothesis, which proposed that the relationship between instant gratification and actual social media use is mediated by style of social media use, such that lower (higher) levels of LDR Proportion lead to using social media more actively (more passively), which in turn lead to a heavier (lower) actual social media use (screen time and pickups). However, the current study explored the style of social media use across a very limited range, as the sample only distinguished between (high versus lower) levels of passive use — while almost no active users were tested. Specifically, only 1 out of 49 participants scored above 0 (i.e., 2.33) on the style of social media use, greatly limiting the interpretation of results. It suggests that participants of the current study may have not associated Instagram use as a potential source of instant rewards because, as shown before in the 'Theoretical Framework', receiving rewards on SM is often the result of an active behavior (e.g., posting). Therefore, passive social media users of the current sample who have a higher preference for instant gratification have not been conditioned to adopt an active style when spending (little time) on Instagram in order to satisfy their need for instant gratification. Consequently, we were not allowed to test the effect of adopting an active style of social media use on Instagram actual use, which as compared to passive style, the active style was found to be associated with increased time spent using SM (Shaw et al., 2021). Future research should target users with an active style of social media use in order to test the mediating effect of the full range in style of social media use.

Sanity-check Hypotheses and Overall Correlations

While we found a significant correlation between self-reported self-control and social media self-control failure (SH2), we found no significant correlation between self-reported self-control and performance-based self-control (SH1), and no significant correlation between self-reported social media self-control failure and performance-based self-control (SH3); indeed, these last two correlations were in the opposite direction. Note that, the observed correlation between self-reported self-control and social media self-control failure (SH2) was large in size. This is higher than in Du et al.'s study (2018), who found a moderate correlation between these two variables. The results suggest that perceiving difficulty to self-control in general may in part (but not necessarily) mean that one has (perceived) difficulty to refrain from using SM when its use conflicts with long-term goals and ongoing tasks at that moment. In contrast, there was no significant correlation between the two self-reported measures of self-control and performance-based self-control. These findings are in part inconsistent with Schmeichel and Zell's study (2007), who found that participants' higher scores on self-reported self-control (i.e., BSCS) predicted lower performance-based self-control (i.e., fewer blinks) while controlling for arousal. Explanation of the findings is two-fold: on the one hand, indeed, participants' performance-based self-control was (likely) not measured accurately — given the limitations found in the online version of the refrain-from-blinking task that we developed (which are described in the section below); on the other hand, it might be that indeed self-report measures do not correlate well with performance-based measures, and can even present an opposite direction effect. This notion is supported by Wiradhany and Koerts (2019), who argued that it is possible to score low in self-report measures (e.g., BSCS) and high (low) in performance-based measures (e.g., Blink Rate), and vice versa. According to the scholars, one thing is individuals' ability at the "functional level", tested in an executive function test as the online version of the refrain-from-blinking task. Another thing is the ability to self-control at the "activities level" in everyday situations. Impairments on the one side do not necessarily lead to impairments on the other side (Wiradhany & Koerts, 2019). Therefore, performance-based measures of self-control might not necessarily assess the same dimensions of self-control as assessed by the self-report questionnaire.

In regards to the overall correlations, most results are not surprising and make intuitive sense. For example, there was a positive correlation between Instagram actual use and smartphone actual use. Also, while older participants reported having spent a longer time (in years) using SM than younger participants, older participants reported having lower difficulty to refrain from using SM (when its usage conflicts with long-term goals and ongoing tasks at that moment) than older participants. These findings suggest a high validity of the data collected among young adults, as well as may encourage future research on age differences in SMU.

Limitations and Recommendations for Future Research

While our data provided valuable insights into the relationship between individual differences and social media-related behaviors, there are some limitations to our design that should be considered for future research. A first limitation has to do with the characteristics of the sample used in the analyses, in particular, the sample size and variability. Limited by time constraints, we were only able to include valid data from 49 participants, which is around half of the sample used in previous studies that the current study aimed to follow up; e.g., Schulz van Endert and Mohr (2020) included 101 participants in the analyses. Moreover, within the already small sample, nine participants reported spending extra time on SM (in general) due to work-related obligations. This suggests that Instagram screen time of nine out of 49 participants might be inflated by their 'obligatory' screen time destined for work-related activities. Therefore, their average daily Instagram screen time might not only be the result of a 'free' choice to use Instagram but also the result of work-related obligations, introducing noise to the data. Furthermore, the sample was not representative in terms of the different styles of SMU, as little to no participants represented an active style of use. As elaborated above, this might explain the significant but opposite correlation found in the relationship between instant gratification and actual social media use, and the lack of the mediating effect of style of social media use in this relationship. Future research should aim for a larger sample size and a more focused selection procedure to cover the full spectrum in style of social media use.

In addition, a second limitation is due to the method used to assess participants' style of social media use. In the same way that self-report measurements of frequency of SMU have limitations in determining users' actual social media use (Parry et al., 2020), the same could be expected in regards to self-report measurements of style of social media use i.e., the adaptive version of Escobar-Viera et al. 's PASMU-scale (2018) used in this study. Some SMU activities may be more easily recalled (e.g., posting) than other activities (e.g., scrolling). Future (experimental) research might consider using the computerized task SNSBT, developed by Shaw et al. (2021), which seems to be more accurate in assessing participants' style of social media use than the self-report questionnaires (Shaw et al., 2021).

Third, the assessment of participants' actual social media use was limited to Instagram actual use. Among the many SM apps that young adults seem to use on a daily basis (e.g., Facebook, Twitter, YouTube, and more recently TikTok; de Best, 2019), only participants' Instagram actual use was included. This was to allow for meaningful analyses that could be performed on the entire sample ($N = 49$). As participants' Instagram actual use is only partly representative of young adults' overall SMU, this constitutes a limitation. Similar to the issue found on participants' style of social media use, limiting analyses of participants' actual social media use to Instagram actual use may justify the significant but opposite correlation found in the relationship between instant gratification and actual social media use. We recommend future research not to target specific SMPs, but to assess actual use of all the platforms among the category of SMPs that the participants reported using. Young adults' actual social media use is complex. They differ substantially in terms of which SMPs they use — numerous platforms in a lot of different combinations, and likely for a multitude of different functions (Griffioen et al., 2021). A holistic approach to youth' actual social media use would allow accounting for all these differences in terms of which SMPs they use, as well as to relate individual differences in preference for instant gratification not only with actual social media use (screen time and pickups), but also to explore relations with the number of SMPs used per participant, and specific combinations of SMPs (e.g., Facebook + Instagram).

Finally, participants' performance-based self-control was not measured in a controlled lab environment and that may limit conclusions on the findings. As opposed to Schmeichel and Zell's study (2007), due to COVID-19 restrictions, participants of the current study were asked to self-employ the refrain-from-blinking task (i.e., the performance-based measure of self-control) from home. Even though efforts were made to replicate the set-up and instructions used in the original study (Schmeichel & Zell, 2007; see instructional video on osf.io/546tg), performing the task from home may have had natural implications on participants' performance. For example, one participant was interrupted by a companion while performing the task, therefore, contrary to the task instructions, he was asked to perform the exercise twice. Also, the researcher's control over the accuracy of the recordings is near to null (Did participants honor the instructions of the task and recorded the refrain-from-blinking task at first try? Or, due to social desirability issues, did they share only their best try among many?). Since circumstances on which the task was performed differed substantially among participants, results may not be really comparable. Furthermore, as opposed to Schmeichel and Zell's study (2007), we were not able to control for participants' arousal when we performed the correlation test between participants' self-reported and performance-based self-control. As the tense-arousal variable did not get an acceptable reliability score (see 'Materials and measures' section). This lower reliability score might be due to participants' difficulties interpreting the meaning of some adjectives, such as "jittery" or "composed". Therefore, inconsistent findings of this study on participants' performance-based self-control might be explained by the limitations found in the administration of the refrain-from-blinking task and subsequent data analysis. Future research using the refrain-from-blinking task as a behavioral measure of self-control should administer the task in the controlled environment of the lab.

Conclusion

While the body of literature on individual differences in functioning and media engagement is growing, still a lot remains unclear and has to be revisited with more objective and in-depth measures on the relationship between individual differences in preference for instant gratification and actual social media use. The current study suggested that there is indeed a significant relationship between instant gratification and participants' actual time spent using social media (i.e., Instagram). However, this effect was opposite to what was expected — the higher was users' preference for instant gratification, the *less* was their Instagram screen time. A possible explanation to this finding involved participants' perceived style of social media use, as well as its implication on their experience with instant rewards when using Instagram. Also, there was no moderating effect of self-reported self-control, performance-based self-control and social media self-control failure on the relationship between instant gratification and actual social media use, nor was there a mediating effect of style of social media use. However, results are not statistically powered enough to draw strong conclusions, and limitations were discussed. Overall, the present study still contributes to a fairly limited understanding of social media-related behaviors of the youth and their individual differences, providing new directions and insights for future research on the relationship between instant gratification and actual social media use.

References

Baumeister, R. F., & Leary, M. R. (1995). *The Need to Belong: Desire for Interpersonal Attachments as a Fundamental Human Motivation*. 33.

Boyd, D. M., & Ellison, N. B. (2007). Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210–230. https://doi.org/10.1111/j.1083-6101.2007.00393.x

Caird, J. K., Johnston, K. A., Willness, C. R., Asbridge, M., & Steel, P. (2014). A meta-analysis of the effects of texting on driving. *Accident Analysis & Prevention*, *71*, 311–318. https://doi.org/10.1016/j.aap.2014.06.005

de Best, R. (2019). *Number of individuals using the leading social media platforms in the Netherlands in 2019, by social network(in million users)*. Statista. https://www.statista.com/statistics/579626/social-media-penetration-in-the-netherlands-by-social-network/

Delaney, D., Stein, L. A. R., & Gruber, R. (2018). Facebook addiction and impulsive decision-making. *Addiction Research & Theory*, *26*(6), 478–486. https://doi.org/10.1080/16066359.2017.1406482

Dreves, P. A., Blackhart, G. C., & McBee, M. T. (2020). Do behavioral measures of self-control assess construct-level variance? *Journal of Research in Personality*, *88*, 104000. https://doi.org/10.1016/j.jrp.2020.104000

Du, J., van Koningsbruggen, G. M., & Kerkhof, P. (2018). A brief measure of social media self-control failure. *Computers in Human Behavior*, *84*, 68–75. https://doi.org/10.1016/j.chb.2018.02.002

Escobar-Viera, C. G., Shensa, A., Bowman, N. D., Sidani, J. E., Knight, J., James, A. E., &

Primack, B. A. (2018). Passive and Active Social Media Use and Depressive Symptoms Among United States Adults. *Cyberpsychology, Behavior, and Social Networking*, *21*(7), 437–443. https://doi.org/10.1089/cyber.2017.0668

Frost, P., Donahue, P., Goeben, K., Connor, M., Cheong, H. S., & Schroeder, A. (2019). An examination of the potential lingering effects of smartphone use on cognition. *Applied Cognitive Psychology*, *33*(6), 1055–1067. https://doi.org/10.1002/acp.3546

Fullwood, C., Quinn, S., Kaye, L. K., & Redding, C. (2017). My virtual friend: A qualitative analysis of the attitudes and experiences of Smartphone users: Implications for Smartphone attachment. *Computers in Human Behavior*, *75*, 347–355. https://doi.org/10.1016/j.chb.2017.05.029

Hadar, A., Hadas, I., Lazarovits, A., Alyagon, U., Eliraz, D., & Zangen, A. (2017). Answering the missed call: Initial exploration of cognitive and electrophysiological changes associated with smartphone use and abuse. *PLOS ONE*, *12*(7), e0180094. https://doi.org/10.1371/journal.pone.0180094

Hanley, S. M., Watt, S. E., & Coventry, W. (2019). Taking a break: The effect of taking a vacation from Facebook and Instagram on subjective well-being. *PLOS ONE*, *14*(6), e0217743. https://doi.org/10.1371/journal.pone.0217743

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach*. Guilford Publications.

Jo Sales, N. (2018). *Swiped: Hooking Up in the Digital Age*. https://www.imdb.com/title/tt8839634/

Kaplan, B. A., Lemley, S. M., Reed, D. D., & Jarmolowicz, D. P. (2014). *21- and 27-Item Monetary Choice Questionnaire Automated Scorers*.

https://kuscholarworks.ku.edu/handle/1808/15424

Keidel, K., Rramani, Q., Weber, B., Murawski, C., & Ettinger, U. (2021). Individual Differences in Intertemporal Choice. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.643670

Kim, S.-K., Kim, S.-Y., & Kang, H.-B. (2016). An Analysis of the Effects of Smartphone Push Notifications on Task Performance with regard to Smartphone Overuse Using ERP. *Computational Intelligence and Neuroscience*, *2016*, e5718580. https://doi.org/10.1155/2016/5718580

Kirby, K. N., Petry, N. M., & Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *Journal of Experimental Psychology. General*, *128*(1), 78–87. https://doi.org/10.1037//0096-3445.128.1.78

Lindström, B., Bellander, M., Schultner, D. T., Chang, A., Tobler, P. N., & Amodio, D. M. (2021). A computational reward learning account of social media engagement. *Nature Communications*, *12*(1), 1311. https://doi.org/10.1038/s41467-020-19607-x

Madden, G. J., Begotka, A. M., Raiff, B. R., & Kastern, L. L. (2003). Delay discounting of real and hypothetical rewards. *Experimental and Clinical Psychopharmacology*, *11*(2), 139–145. https://doi.org/10.1037/1064-1297.11.2.139

Madden, G., Raiff, B., Lagorio, C. H., Begotka, A. M., Mueller, A. M., Hehli, D., & Wegener, A. A. (2004). Delay discounting of potentially real and hypothetical rewards: II. Between- and within-subject comparisons. *Experimental and Clinical Psychopharmacology*. https://doi.org/10.1037/1064-1297.12.4.251

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, *50*(4), 370–396. https://doi.org/10.1037/h0054346

Matthews, G., Jones, D. M., & Chamberlain, A. G. (1990). Refining the measurement of mood: The UWIST Mood Adjective Checklist. *British Journal of Psychology*, *81*(1), 17–42. https://doi.org/10.1111/j.2044-8295.1990.tb02343.x

Meshi, D., Morawetz, C., & Heekeren, H. R. (2013). Nucleus accumbens response to gains in reputation for the self relative to gains for others predicts social media use. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00439

Meshi, D., Tamir, D. I., & Heekeren, H. R. (2015). The Emerging Neuroscience of Social Media. *Trends in Cognitive Sciences*, *19*(12), 771–782. https://doi.org/10.1016/j.tics.2015.09.004

Montag, C., Markowetz, A., Blaszkiewicz, K., Andone, I., Lachmann, B., Sariyska, R., Trendafilov, B., Eibes, M., Kolb, J., Reuter, M., Weber, B., & Markett, S. (2017). Facebook usage on smartphones and gray matter volume of the nucleus accumbens. *Behavioural Brain Research*, *329*, 221–228. https://doi.org/10.1016/j.bbr.2017.04.035

Moreira, D., & Barbosa, F. (2019). Delay discounting in impulsive behavior: A systematic review. *European Psychologist*, *24*(4), 312–321. https://doi.org/10.1027/1016-9040/a000360

Myerson, J., Baumann, A. A., & Green, L. (2014). Discounting of delayed rewards: (A)theoretical interpretation of the Kirby questionnaire. *Behavioural Processes*, *107*, 99–105. https://doi.org/10.1016/j.beproc.2014.07.021

Odgers, C. L., Schueller, S. M., & Ito, M. (2020). Screen Time, Social Media Use, and Adolescent Development. *Annual Review of Developmental Psychology*, *2*(1), 485–502. https://doi.org/10.1146/annurev-devpsych-121318-084815

Ohme, J., Araujo, T., de Vreese, C. H., & Piotrowski, J. T. (2021). Mobile data donations: Assessing self-report accuracy and sample biases with the iOS Screen Time function.

Mobile Media & Communication, *9*(2), 293–313. https://doi.org/10.1177/2050157920959106

Orben, A. (2020). Teenagers, screens and social media: A narrative review of reviews and key studies. *Social Psychiatry and Psychiatric Epidemiology*, *55*(4), 407–414. https://doi.org/10.1007/s00127-019-01825-4

Parry, D., Davidson, B. I., Sewall, C., Fisher, J. T., Mieczkowski, H., & Quintana, D. S. (2020). *A Systematic Review and Meta-Analysis of Discrepancies Between Logged and Self-Reported Digital Media Use* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/f6xvz

Paschke, K., Austermann, M. I., Simon-Kutscher, K., & Thomasius, R. (2021). Adolescent gaming and social media usage before and during the COVID-19 pandemic. *SUCHT*, *67*(1), 13–22. https://doi.org/10.1024/0939-5911/a000694

Petropoulos Petalas, D., Konijn, E. A., Johnson, B. K., Veldhuis, J., Bij de Vaate, N. A. J. D., Burgers, C., Droog, E., Międzobrodzka, E., Balint, K. E., & van de Schoot, R. (2021). Plurality in the Measurement of Social Media Use and Mental Health: An Exploratory Study Among Adolescents and Young Adults. *Social Media + Society*, *7*(3), 20563051211035350. https://doi.org/10.1177/20563051211035353

Pontes, H. M. (2020). Critically appraising the pitfalls of screen time effects research. *Australian & New Zealand Journal of Psychiatry*, 0004867420963736. https://doi.org/10.1177/0004867420963736

Rademacher, L., Salama, A., Gründer, G., & Spreckelmeyer, K. N. (2014). Differential patterns of nucleus accumbens activation during anticipation of monetary and social reward in young and older adults. *Social Cognitive and Affective Neuroscience*, *9*(6), 825–831. https://doi.org/10.1093/scan/nst047

Rideout, V., & Fox, S. (2018). Digital Health Practices, Social Media Use, and Mental Well-Being Among Teens and Young Adults in the U.S. *Articles, Abstracts, and Reports*. https://digitalcommons.psjhealth.org/publications/1093

Rusz, D., Le Pelley, M. E., Kompier, M. A. J., Mait, L., & Bijleveld, E. (2020). Reward-driven distraction: A meta-analysis. *Psychological Bulletin*, *146*(10), 872–899. https://doi.org/10.1037/bul0000296

Schmeichel, B. J., & Zell, A. (2007). Trait Self‐Control Predicts Performance on Behavioral Tests of Self‐Control. *Journal of Personality*, *75*(4), 743–756. https://doi.org/10.1111/j.1467-6494.2007.00455.x

Schulz van Endert, T., & Mohr, P. N. C. (2020). Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting. *PLOS ONE*, *15*(11), e0241383. https://doi.org/10.1371/journal.pone.0241383

Shaw, D., Pennington, C. R., Ngombe, N., Kessler, K., & Kaye, L. K. (2021). *It's not what you do, it's the way that you do it: An experimental task delineates among styles of behaviour on social networking sites and psychosocial measures.* PsyArXiv. https://doi.org/10.31234/osf.io/ztkmv

Sherman, L. E., Hernandez, L. M., Greenfield, P. M., & Dapretto, M. (2018). What the brain 'Likes': Neural correlates of providing feedback on social media. *Social Cognitive and Affective Neuroscience*, *13*(7), 699–707. https://doi.org/10.1093/scan/nsy051

Sherman, L. E., Payton, A. A., Hernandez, L. M., Greenfield, P. M., & Dapretto, M. (2016). The Power of the Like in Adolescence: Effects of Peer Influence on Neural and Behavioral Responses to Social Media. *Psychological Science*, *27*(7), 1027–1035. https://doi.org/10.1177/0956797616645673

Skinner, B. F. (1948). “Superstition” in the pigeon. *Journal of Experimental Psychology*, *38*(2), 168–172. https://doi.org/10.1037/h0055873

Social media fact sheet. (2019, December 6). Demographics of Social Media Users and Adoption in the United States. *Pew Research Center: Internet, Science & Tech*. https://www.pewresearch.org/internet/fact-sheet/social-media/

Staff, R. (2017, February 7). *Full transcript: Time Well Spent founder Tristan Harris on Recode Decode*. Vox. https://www.vox.com/2017/2/7/14542504/recode-decode-transcript-time-well-spent-founder-tristan-harris

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (Second edition). The MIT Press.

Tang, Z., Zhang, H., Yan, A., & Qu, C. (2017). Time Is Money: The Decision Making of Smartphone High Users in Gain and Loss Intertemporal Choice. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00363

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. *Journal of Personality*, *72*(2), 271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x

Tristan, H. (2019, October 16). *How Technology is Hijacking Your Mind—From a Magician and Google Design Ethicist*. https://medium.com/thrive-global/how-technology-hijacks-peoples-minds-from-a-magician-and-google-s-design-ethicist-56d62ef5edf3

Vanden Abeele, M. M. P. (2020). Digital Wellbeing as a Dynamic Construct. *Communication Theory*, qtaa024. https://doi.org/10.1093/ct/qtaa024

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*(5), 1607–1614. https://doi.org/10.3758/s13423-016-1011-z

Wilmer, H. H., Hampton, W. H., Olino, T. M., Olson, I. R., & Chein, J. M. (2019). *Wired to be connected? Links between mobile technology engagement, intertemporal preference and frontostriatal white matter connectivity*. 13.

Wilmer, H. H., Sherman, L. E., & Chein, J. M. (2017). Smartphones and Cognition: A Review of Research Exploring the Links between Mobile Technology Habits and Cognitive Functioning. *Frontiers in Psychology*, *8*, 605. https://doi.org/10.3389/fpsyg.2017.00605

Wiradhany, W., & Koerts, J. (2019). Everyday functioning-related cognitive correlates of media multitasking: A mini meta-analysis. *Media Psychology*, *24*(2), 276–303. https://doi.org/10.1080/15213269.2019.1685393

Zhang, W., & Zhang, L. (2012). Explicating multitasking with computers: Gratifications and situations. *Computers in Human Behavior*, *28*(5), 1883–1891. https://doi.org/10.1016/j.chb.2012.05.006

Appendices

Appendix A: 27-item Monetary Choice Questionnaire (MCQ; Kirby et al., 1999)

"For each of the following 27 choices, please indicate which reward you would prefer: the smaller reward today, or the larger reward in the specified number of days. Please note that there are no wrong or right answers."

1. What would you prefer to get? €54 today, or €55 in 117 days?
2. What would you prefer to get? €55 today, or €75 in 61 days?
3. What would you prefer to get? €19 today, or €25 in 53 days?
4. What would you prefer to get? €31 today, or €85 in 7 days?
5. What would you prefer to get? €14 today, or €25 in 19 days?
6. What would you prefer to get? €47 today, or €50 in 160 days?
7. What would you prefer to get? €15 today, or €35 in 13 days?
8. What would you prefer to get? €25 today, or €60 in 14 days?
9. What would you prefer to get? €78 today, or €80 in 162 days?
10. What would you prefer to get? €40 today, or €55 in 62 days?
11. What would you prefer to get? €11 today, or €30 in 7 days?
12. What would you prefer to get? €67 today, or €75 in 119 days?
13. What would you prefer to get? €34 today, or €35 in 186 days?
14. What would you prefer to get? €27 today, or €50 in 21 days?
15. What would you prefer to get? €69 today, or €85 in 91 days?
16. What would you prefer to get? €49 today, or €60 in 89 days?
17. What would you prefer to get? €80 today, or €85 in 157 days?
18. What would you prefer to get? €24 today, or €35 in 29 days?
19. What would you prefer to get? €33 today, or €80 in 14 days?
20. What would you prefer to get? €28 today, or €30 in 179 days?
21. What would you prefer to get? €34 today, or €50 in 30 days?
22. What would you prefer to get? €25 today, or €30 in 80 days?
23. What would you prefer to get? €41 today, or €75 in 20 days?
24. What would you prefer to get? €54 today, or €60 in 111 days?
25. What would you prefer to get? €54 today, or €80 in 30 days?
26. What would you prefer to get? €22 today, or €25 in 136 days?
27. What would you prefer to get? €20 today, or €55 in 7 days?

Note. In this study, the original currency i.e., the dollar ($) was changed to euros (€), as the present questionnaire was likely to be filled in by participants living or studying in Europe.

Appendix B: Screenshots

Figure 2.

An example of participants' screenshots from the Screen Time app.

Note. The screen time values presented right after the application names are the total number of hours and minutes that the participant spent on each application during the past week, seven days. This screenshot is a rare example of a participant who uses all the four social media apps (Instagram, TikTok, Twitter and Facebook) which are included in the 'Social' category according to the iOS criteria. YouTube is categorized as an entertainment app, that is why it is not present in these screens.

Appendix C: The Brief Self-control Scale (BSCS; Tangney et al., 2004)

1. I am good at resisting temptation
2. I have a hard time breaking bad habits
3. I am lazy
4. I say inappropriate things
5. I do certain things that are bad for me, if they are fun
6. I refuse things that are bad for me
7. I wish I had more self-discipline
8. People would say that I have iron self-discipline
9. Pleasure and fun sometimes keep me from getting work done
10. I have trouble concentrating
11. I am able to work effectively toward long-term goals
12. Sometimes I can't stop myself from doing something, even if I know it is wrong
13. I often act without thinking through all the alternatives

Note. The items 2, 3, 4, 5, 7, 9, 10, 12, 13 were reverse-scored.

Appendix D: Adapted version of the Passive Active Social Media Use scale (PASMU-scale; Escobar-Viera et al., 2018)

Table 2.

An adapted version of the Passive Active Social Media Use scale (PASMU-scale).

	Never	Less than once a week	Once a week	2–6 times a week	Once a day	Several times a day
Scroll through the newsfeed						
Read comments/reviews						
Watch videos or view pictures						
Share others' content (e.g., retweet, share posts or status updates)						
Comment on, or respond to someone else's content {e.g., replying to a story, a post, participating in a poll, comment a picture}						
Post your own content (e.g., tweet, status update, post stories, photos etc)						