Screen time and impulsivity

Exploring the association between use of digital devices and delay discounting

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Erklärung über die Zusammenarbeit mit Ko-Autoren

Der Hauptteil dieser Dissertation basiert inhaltlich auf den oben aufgelisteten drei Studien. Zwei von diesen Studien (1. und 3.) wurden mit Prof. Dr. Peter N.C. Mohr als Ko-Autor verfasst. Eine Studie (2.) wurde vom Autor alleine verfasst. Die Zusammenfassungen dieser Studien, welche im Hauptteil dieser Dissertation zu finden sind, wurden ohne Mithilfe des Ko-Autors verfasst. Ebenso wurden alle weiteren Teile dieser Dissertation alleine vom Autor verfasst.

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1. Summary

The choice between enjoying meals at McDonald's and a fit physique, between smoking cigarettes and healthy lungs or between scrolling through social media and finishing a dissertation - all these ubiquitous decision tasks require humans to trade off costs and benefits at different points in time and are referred to as intertemporal choices. Economists started investigating these trade-offs as early as in the 18th century, yet focusing on the impact of intertemporal choices on economic prosperity instead of on diet, health or academic achievement. Despite early differentiated considerations, a simple theory of intertemporal choice was introduced and quickly adopted in the first half of the 20th century, namely Discounted Utility theory. At its core lies a model which posits that humans choose the option which maximizes the sum of discounted utility flows associated with that option. The explicit and implicit assumptions of the Discounted Utility model, which was not founded on empirical evidence, were finally subjected to scrutiny by psychologists by means of field studies and experiments in the second half of the 20th century. Numerous behavioral anomalies were discovered, which resulted in the development of alternative models, such as hyperbolic discounting, which have markedly higher descriptive validity. Since then, research on intertemporal choice has flourished and produced many valid accounts for various behavioral phenomena. For instance, more often than typically desired, a so-called impulsive choice is made in favor of a smaller but sooner reward (e.g. a Big Mac), thereby forgoing a larger but delayed reward (e.g. a flat belly). Behavioral economists have proposed a key process underlying this decision: delay discounting, i.e. the tendency to discount future rewards depending on their delay. Delay discounting, often simplistically referred to as impulsivity, has been shown to have both trait- and state-like characteristics; people have a stable, partially genetically determined baseline tendency to discount future rewards that may adapt slightly depending on the decision context. Furthermore, neuroscientists have recently begun to investigate the neural mechanisms underlying delay discounting and currently propose the valuation of rewards, cognitive control and prospection as relevant subprocesses. Another finding of high clinical relevance is that delay discounting is associated with numerous problematic behaviors, which include substance abuse but also behavioral addictions.

In parallel, digital devices, such as smartphones, tablets and laptops/PCs, have permeated societies worldwide. Notably, adults' and even children's usage of these technologies is often characterized as excessive or, as some researchers propose, addictive. This has begged the question if there is a link between digital device use and delay discounting, i.e. to what extent may smartphone, tablet and laptop/PC use be considered an impulsive choice? The research within this dissertation has contributed three empirical investigations to this young literature. In study 1, we sought to replicate initial findings of a link between smartphone use and impulsivity using more reliable and nuanced methods. Following recent insights on the neural mechanisms underlying intertemporal choice, we also analyzed the role of reward responsiveness, self-control and consideration of future consequences. We found that students' actual smartphone use was correlated with delay discounting and that this relationship was driven by social media and gaming applications. Furthermore, neither psychological variable mediated the relationship between use of smartphones and the degree of discounting. Study 2 investigated the link between delay discounting and children's addictive use of digital devices, i.e. use with negative social, psychological, physical and educational consequences. Associations with children's self-control as well as academic performance were also analyzed. The results showed that children's preference for smaller, immediate rewards was related to a greater degree of addictive digital device use, but that this relationship was confounded by children's ability to control their thoughts, emotions and behavior. Additionally, self-control and screen time predicted children's most recent grade average. Examining delay discounting in the context of a central aspect of digital device use, namely social media rewards, was the goal of study 3. We found that the magnitude effect of delay discounting, i.e. delay discounting decreases with increasing reward magnitude, also applies to Instagram followers and likes. Moreover, the degrees of discounting of money, followers and likes were correlated, providing further evidence for the trait component of delay discounting. Taken together, this research has demonstrated a significant albeit weak association between digital device use and impulsive choice. The causal direction of this relationship remains unresolved, but self-control seems to promote avoidance of harmful outcomes associated with use of digital devices, particularly in children. The studies have also pointed out the importance of adopting a nuanced view on digital device use in future research, with a particular focus on its reward mechanisms.

2. Glossary

Behavioral addiction A behavior producing short-term gratification that may instigate persistent behavior despite awareness of negative consequences (e.g. gambling) (Grant et al., 2010)

Cognitive control A neural process which prioritizes information for goal-driven decision-making (Macki et al., 2013). One of at least three mechanisms underlying intertemporal choice (Peters and Büchel, 2011)

Consideration of future consequences A psychological construct, which is a stable individual difference in the degree to which humans consider future vs. immediate consequences of potential behaviors (Strathman et al., 1994)

Delay discounting The psychological process by which outcomes are devalued with increasing delay (Odum, 2011b)

Discounted Utility (DU) model An economic model of intertemporal choice postulating that humans choose options which maximize the sum of their discounted utility flows (Samuelson, 1937)

Exponential discounting An assumption implied in the Discounted Utility model which posits that future utilities are devalued at constant rate (Chabris et al., 2010)

Hyperbolic discounting A behavioral model of intertemporal choice which posits that human and non-human animals' delay discounting behavior follows a hyperbolic function (Ainslie, 1975)

Impulsivity The tendency to act swiftly without due deliberation or to choose short-term over long-term rewards (Evenden, 1999)

Intertemporal choice A choice involving tradeoffs of costs and benefits occurring at different points in time (Loewenstein et al., 2003)

Prospection A neural process by which future experiences are vividly imagined. One of at least three mechanisms underlying intertemporal choice (Peters and Büchel, 2011)

Reward responsiveness The ability to experience pleasure in the anticipation and receipt of rewards (Taubitz et al., 2015)

Reward valuation A neural process responsible for the representation of subjective value of outcomes. One of at least three mechanisms underlying intertemporal choice (Peters and Büchel, 2011)

Self-control The ability to align thoughts, emotions and behavior with internal goals (Tangney et al., 2004)

Temporal discounting see delay discounting

Quasi-hyperbolic discounting A behavioral model of intertemporal choice which amends exponential discounting by including a present bias parameter (Laibson, 1997)

3. Introduction

Should I begin writing this dissertation now or browse through social media in the hopes of finding yet another silly animal video? The first choice implies forgoing primitive and (most likely) short-lived but immediately available entertainment for the sake of progressing towards the reverend but distant goal of completing my doctoral studies. While most people would consider the latter outcome as clearly superior, the decision did not come about easily - even after having studied intertemporal choices, i.e. decisions requiring people to trade off costs and benefits at different points in time, for the past three years. A plausible explanation for this conflict between smaller, sooner rewards and larger, delayed rewards has been proposed by behavioral economists; human and non-human animals (and apparently academic researchers) discount future rewards as a function of the delay towards their receipt - a process which is referred to as delay (or temporal) discounting (Mazur, 1987). This tendency causes future rewards, such as retirement savings, healthy lungs or global non-warming to be discounted in such a way that they appear similarly or even less attractive compared to smaller, immediate rewards, such as shopping, smoking or continuing activities that produce large CO_2 emissions. Thus, oftentimes a so-called impulsive choice is made to the detriment of more beneficial future outcomes.

Due to its wide-ranging applications, delay discounting has been studied extensively by economists (e.g. Samuelson, 1937), sociologists (e.g. Straus, 1962), psychologists (e.g. Ainslie, 1975), and more recently neurobiologists (e.g. Kable and Glimcher, 2007). One of the key findings is that delay discounting behavior is a stable individual difference, which shares many of the features of a personality trait (Odum, 2011a). For this reason, delay discounting is often simplistically referred to as impulsivity (Madden and Bickel, 2010); a person that strongly discounts future outcomes is considered to be impulsive. Another central insight from the literature is that delay discounting is a reliable predictor of a host of maladaptive behaviors, such as drug abuse (Reynolds, 2006), alcoholism (Petry, 2001a), overeating (Epstein et al., 2010) or gambling (Alessi and Petry, 2003). Individuals exhibiting addictive behavior typically discount future rewards more extremely than controls (MacKillop et al., 2011). With this knowledge in mind, let us circle back to the initial decision problem of engaging with my smartphone versus writing these lines.

Virtually every adult in the developed world - more than 80% of the global population according to Statista (2022) - owns a smartphone. Further, they are not just owned and safely stored in a drawer. On the contrary, while the numbers vary depending on the population surveyed, people's average screen time ranges from around 4 hours (Statista, 2021) to almost 6 hours per day (Solitaired, 2021). Even though a portion of this screen time is constituted by productive activities (e.g. writing e-mails or doing research), the majority of surveys indicate that social media, gaming and messaging applications are being used the longest, especially among adolescents and younger adults. Also, 40% of American teens state that they check their phone within five minutes before going to bed, 32% check it within five minutes after waking up and 36% report that they use their device at least once during the night (Robb, 2019). These impressive statistics have led some researchers to hypothesize that prolonged usage of digital devices (i.e. smartphones, tablets and laptops/PCs) may alter human cognition over time (Wilmer et al., 2017). At the same time, other researchers have linked excessive screen time to adverse outcomes, such as lower sleep quality and quantity (Hale and Guan, 2015), heightened stress (Vahedi and Saiphoo, 2018), decreased physical activity (Duncan et al., 2012) or lower academic performance (Adelantado-Renau et al., 2019). It seems that digital device use, while definitely useful and rewarding the moment they’re being used, implies a risk of negative consequences in the long run. May interaction with digital technologies thus be considered an impulsive choice?

This is the central question which inspired the research of this dissertation. To approach this issue, initially, the key findings in the literature on intertemporal choice and delay discounting shall be presented in section 3.1. Subsequently, the case will be made for a new field of application, namely digital device use, along with a brief overview of existing research on its relationship with cognition in general and more specifically with impulsive decision-making (section 3.2). This will enable the identification of gaps from which the research questions of this dissertation (section 3.3) will be derived. Chapter 4, the core of this dissertation, then provides a summary of three empirical studies which sought to address the previously identified research questions. The findings of these studies will be discussed in chapter 5, followed by a more general reflection on the knowledge gain of this dissertation research and the remaining and newly emerged open questions.

3.1 Intertemporal choice and delay discounting

3.1.1 Origins: The Discounted Utility model

Intertemporal choices are decisions which require trade-offs of costs and benefits occurring at different time periods. These decisions are inherent to human life, as consequences of actions always play out over time. As early as in the 18th century, Adam Smith was the first economist known to recognize the importance of intertemporal choices in determining the economic prosperity of nations (Loewenstein et al., 2003). His successors then sought to understand, mostly based on introspection and observation, the sociological and psychological factors underlying intertemporal choice. They identified the fundamental property of preferring immediate utility over delayed utility, i.e. time preference, and also proposed its determinants, namely the excitement associated with immediate consumption, the exercise of self-restraint in the face of such arousal and the ability to imagine future wants (Loewenstein et al., 2003). Astonishingly, almost two centuries later three very related processes, albeit coined slightly differently, are investigated by neuroscientists as mechanisms underlying intertemporal choice: reward valuation, cognitive control and prospection (Peters and Büchel, 2011), which will be highlighted in section 3.1.6.

In spite of these early differentiated considerations, in the first half of the 20th century economist Paul Samuelson introduced a rather simple model of intertemporal choice, the Discounted Utility (DU) model (Samuelson, 1937). The DU model merged the various aforementioned psychological motives into one parameter, the discount rate, and otherwise relied upon the idea that the total utility of a choice can be represented by a weighted sum of utility flows associated with that choice at each point in time (Chabris et al., 2010).

$$U_t(c_t, \ldots, c_T) = \sum_{k=0}^{T-t} \left(\frac{1}{1+r}\right)^k \cdot u(c_{t+k})$$

Equation 1. Discounted Utility model

In this formula, U_t represents the total utility at period t, T being the last period of life.$u(c_{t+k})$ is the utility flow in period $t+k$, which is discounted based on an individual's discount rate r. According to this model, when facing intertemporal choice options a decision-maker simply chooses the option which maximizes the sum of its discounted utility flows. Unsurprisingly, the DU model shows significant resemblance to another popular decision theory of classical economics, namely Expected Utility Theory (Morgenstern and von Neumann, 1953).[1] While Samuelson himself had doubts with regard to the normative and descriptive validity of his model, thanks to its simplicity and elegance, it quickly became the prevalent model for the analysis of intertemporal choice and remains a popular account for economists to this day (Loewenstein et al., 2003). It is based on a series of implicit psychological assumptions, of which two central ones shall be briefly highlighted in order to be able to recognize its merit - or lack thereof - as a descriptive model of behavior.

Constant discount rate and exponential discounting

As exhibited by the discount factor $D(k) = \delta^k$ with $\delta = (\frac{1}{1+r})$, a constant discount rate r is assumed throughout all periods, which is compounded over delay k (Frederick et al., 2002). This exponential discount function implies that a person shows time (or dynamic) consistency: if she prefers option A in one day to B in two days, she will also prefer option A in a year and one day to B in a year and two days. Furthermore, DU prescribes that, as long as goods are exchangeable, the discount rate remains identical between them, e.g. apples and cigarettes have the same discount rate (Chapman, 1996).

Utility and consumption independence

Another assumption of DU is that only overall utility (the sum of discounted utility flows) matters in intertemporal choice, i.e. it is independent of the distribution of utility across time (Frederick et al., 2002). Hence, a decision-maker will be indifferent between e.g. a choice with larger utility flows earlier in time and a choice with larger utility flows in the distant future, as long as the sum of the discounted flows of both is identical. Further, the consumption independence assumption states that the utility of an outcome is not affected by outcomes experienced in earlier or later periods (Frederick

[1] Readers familiar with financial economics will also recognize the conceptual overlap with discounted cash flow (DCF) analysis, which is used to value an investment that produces future cash in- and outflows. Here, the net present value of an investment is calculated by summing up its future cash flows, which are also discounted with a constant rate over time.

et al., 2002). For instance, a person's choice of breakfast yesterday or that of tomorrow has no influence on today's choice.

While the DU model makes additional assumptions, at this point the reader will most likely have already developed doubts about the ability of the model to accurately explain real-life behavior. These intuitive doubts are in fact justified, as many of the assumptions of DU have been subject to empirical investigation in the last decades and have overwhelmingly been found to diverge from actual behavior (Loewenstein and Thaler, 1989). Those deviations from normative theory were coined anomalies by psychologists and shall be presented in section 3.1.3. Initially, however, it is helpful to gain an understanding of the methods used by researchers to investigate actual intertemporal choice behavior.

3.1.2 Empirical approaches: methods to study intertemporal choice

The DU model was not founded on empirical evidence. Rather, researchers could solely show that it could be mathematically derived from a set of specific axioms (see Koopmans, 1960). However, roughly forty years after the DU model was first introduced researchers began to test its explicit and implicit assumptions (Frederick et al., 2002). The approaches can be divided into field studies and experiments, the latter nowadays being the dominant way to observe intertemporal choice behavior.

Early field studies investigated the discount rate implied by purchasing decisions of home appliances, such as air conditioners (Hausman, 1979), freezers (Ruderman et al., 1987) or refrigerators (Gately, 1980). Specifically, researchers observed consumers' trade-off between the purchase price of energy-efficient appliances and delayed energy costs. Relatively higher discount rates were inferred from choices in favor of cheaper but less efficient products (with thus higher operating costs in the future). Other studies (e.g. Viscusi and Moore, 1989; Moore and Viscusi, 1990) analyzed people's occupational choices with respect to their risk of fatal and non-fatal injury and the associated premium reflected in salaries. Here, individuals make a trade-off between a higher salary and higher life expectancy; those who tended to opt for lower salaries in favor of longer average lives associated with less risky jobs thus exhibited lower discount rates. Lastly, macroeconomic approaches examining people's life-cycle saving behavior were also taken to estimate discount rates, featuring a plethora of assumptions in their structural models (Frederick et al., 2002). All these field studies had the advantage of providing insights based on real-life behavior but also suffered from a lack of control over confounding variables, such as risk or the nature of the trade-off (losses vs. gains, money vs. health etc.).

In contrast, experiments, in which participants are prompted to complete systematically designed intertemporal tasks, allowed researchers to better isolate effects of interest. The most widely used procedures are matching tasks and choice tasks involving real or hypothetical payoffs. All have in common the experimental variables of a smaller, sooner reward, a larger, later reward and a delay length. In matching tasks (e.g. Ahlbrecht and Weber, 1997), participants are presented with an immediately available payoff and are then asked to state the amount, which has a specified delay, that would make them indifferent between the two options (e.g. USD10 today = USD? in 30 days). Alternatively, a delayed amount is provided and participants are prompted to provide the immediate equivalent or both amounts are given and the participant has to fill in their preferred delay. These procedures enable the researcher to directly calculate a discount rate from, theoretically, a single response. These discount rates, however, turned out to be rather imprecise and to vary enormously depending on the procedure, mostly due to participants employing simple calculations or being unable or unwilling to provide realistic responses especially for long delays or large magnitudes (Frederick et al., 2002). This led to the development of choice tasks, where participants are asked to repeatedly choose between a smaller, sooner or a larger, later reward. In earlier studies (e.g. Kirby and Marakovic, 1996; Kirby et al., 1999; Madden et al., 1997) using paper-and-pencil questionnaires the reward amounts and delays were fixed so that an individual discount rate was inferred based on the pattern of responses. More recent experiments (e.g. Johnson and Bickel, 2002; Green et al., 2007; Du et al., 2002) have also employed computer-based tasks that adjust the reward amounts or delays depending on the participant's previous responses (titration procedure) to elicit precise indifference points. The responses can then be analyzed by means of theoretical models (e.g. exponential discounting or alternatives, see section 3.1.4) or by relying on an atheoretical measure, such as the simple proportion of choices of the larger, delayed reward (LDR proportion). This measure has been shown to be reliable, valid and practical (Myerson et al., 2014) for analyzing responses from the Monetary Choice Questionnaire (Kirby et al., 1999), a widely used intertemporal choice task. Researchers have used both real and hypothetical payoffs, with no significant differences in results (Lagorio and Madden, 2005). This convenient finding has been attributed to the lack of "right" vs. "wrong" or socially desirable responses in intertemporal choice tasks, which promotes unbiased choice behavior (Odum, 2011a).

This section has highlighted the tools and procedures used by intertemporal choice researchers to examine actual behavior, which have allowed them to critically evaluate the assumptions made by Discounted Utility theory. Experiments have emerged as the preferred method and the intriguing findings of these empirical investigations shall be presented in the next section.

3.1.3 Behavioral anomalies

An anomaly is an empirical finding that is not in accordance with predictions made by an established theory (Kuhn, 1970). A host of studies by both economists and psychologists have found several such anomalies vis-a-vis the Discounted Utility model in the last three decades. Many have centered around DU's pivotal assumption of a single discount rate that should be applied across contexts, time and rewards. The key systematic deviations from this normative standard shall be described in the following paragraphs.

<u>Non-exponential discounting</u>

When observing people's intertemporal choices across a span of delay lengths, it has been shown that discount rates do not remain constant but decline as the delay increases (e.g. Benzion et al., 1989; Thaler, 1981; Chapman and Elstein, 1995; Pender; 1996). Furthermore, when mathematical models are fit to these data, discounting behavior is described more accurately by a hyperbolic function instead of the exponential function postulated by DU (e.g. Mazur, 1987; Rachlin et al., 1991; Bickel et al., 1999; Kirby, 1997; Madden et al., 2003). This implies the striking behavioral phenomenon of preference reversal, where people make dynamically inconsistent choices. For instance, most people prefer one apple today over two apples tomorrow, but when offered one apple in a year's time or two apples in a year and one day, they are happy to wait another day for the additional apple. Outside of the lab people display this inconsistency when they fail to stick to healthy diets they once committed to, when they resume smoking after vowing to quit or when they engage in unsafe sex despite previous intentions, to name a few examples.

Magnitude effect

Discount rates vary not only depending on the delay but also on the magnitude of the reward to be discounted. Specifically, discounting decreases as reward size increases (e.g. Thaler, 1981; Benzion et al., 1989; Green et al., 1994; Kirby et al., 1999). This well-documented effect, which has mainly been studied using monetary rewards, is further investigated in this dissertation research in the context of rewards from the digital age (see study 3).

Sign effect

Discounting behavior has not only been studied with positive (i.e. gains) but also with negative outcomes (i.e. losses). In these studies, participants were relatively more willing to accept delayed rewards rather than to incur comparable losses, thereby exhibiting lower discount rates for losses (e.g. Benzion et al., 1989, Redelmeier and Heller, 1993; Baker et al., 2003). This behavior becomes evident in real-life situations when people pay off bills, mortgages and loans earlier than necessary and financially beneficial, partly due to debt aversion (Loewenstein and Thaler, 1989).

Domain (or commodity) effect

Researchers have also investigated possible differences in discount rates due to the commodity being discounted. Contrary to DU's conjecture that a single discount rate should be applied for freely exchangeable commodities, people show a large variety of discount rates for money, health, consumables or entertainment (e.g. Chapman, 1996, Chapman and Elstein, 1995; Odum and Rainaud, 2003; Holt et al., 2016). One pattern, which has emerged from this line of research, is that monetary outcomes are discounted less steeply than non-monetary rewards (see Odum et al., 2020 for a comprehensive review and hypotheses for this phenomenon).

Framing effect

A more recent strand of the literature found robust effects of framing of outcome and delay on discount rates. For instance, Grace and McLean (2005) found that individuals discounted less steeply when the amount of the larger, delayed reward was framed as the smaller, immediate reward plus a bonus. DeHart and Odum (2015) compared discount rates between tasks in which the delay was framed as a specific date (e.g. June 1) vs. as a delay (e.g. in 30 days) and concluded that date framing resulted in shallower discounting. Lastly, Benzion et al. (1989) and Shelley (1993) reported that people discounted more extremely when the time interval between two rewards was framed as a delay as opposed to an acceleration.

Other anomalies

Behavior inconsistent with the assumptions of utility and consumption independence have also been observed. When evaluating sequences of outcomes (e.g. salary development), people generally prefer improving sequences over declining ones even when the sum of both is identical (Hsee et al., 1991; Loewenstein and Prelec, 1993; Ariely and Carmon, 2000). Loewenstein and Prelec (1993) also found a preference for spread in a sequence of consumption; in their experiments, participants tended to prefer longer intervals in between two fancy dinners to having them in close temporal separation.

Based on the vast empirical evidence gathered over the past five decades, researchers from various disciplines have acknowledged that the Discounted Utility model has little descriptive validity. Furthermore, it may even be questioned if the described anomalies are truly judgment errors (is constant discounting rational?), thereby placing doubts on the presumption that DU qualifies as a normative theory (Frederick et al., 2002). This criticism has led to the development of alternative theories, which will be the theme of the next section.

3.1.4 Alternatives: Quasi-hyperbolic and hyperbolic discounting

Beginning in the 1950s, economists first acknowledged the need for intertemporal choice models that better described actual human behavior. In particular, researchers sought an alternative to exponential discounting, which represented the only case in which decision-makers make time-consistent choices (Strotz, 1955). Phelps and Pollak (1968) first introduced the quasi-hyperbolic discount function:

$$D(k) = 1 \qquad \text{if } k = 0$$
$$D(k) = \beta \cdot \delta^k \text{ if } k > 0$$

Equation 2. Quasi-hyperbolic discounting function

What at first glance looks like a crude adaptation of the exponential discounting function can in fact account for time-inconsistent choices as well as present bias, i.e. discounting is higher close to the present and lower in the long run (Laibson, 1997). This is due to the added parameter β which, for values < 1, has the effect that all outcomes beyond the present time get discounted more than under exponential discounting. While the quasi-hyperbolic function represents a radical improvement versus the DU model, it nevertheless cannot explain important phenomena such as the sign effect or preference for improving sequences (Wilkinson & Klaes, 2017).

A further model particularly popular among psychologists describes discounting behavior using a hyperbolic function:

$$D(k) = \frac{1}{(1 + rk)}$$

Equation 3. Hyperbolic discounting function

This discount factor, where r is a free parameter representing an individual's discount rate, is simply multiplied by the delayed reward amount[2] to determine its subjective present value. Hyperbolic discounting was first proposed by Mazur (1987) in a study of pigeons. Meanwhile numerous studies with human participants from various populations concluded that this function provides a significantly better fit than the exponential function traditionally preferred by economists (McKerchar, 2009; Odum, 2011a). Figure 1 displays the three dominant discounting functions in the literature with calibrated parameters.

[2] Remarkably, most delay discounting studies implicitly equalize the amount and utility of a reward.

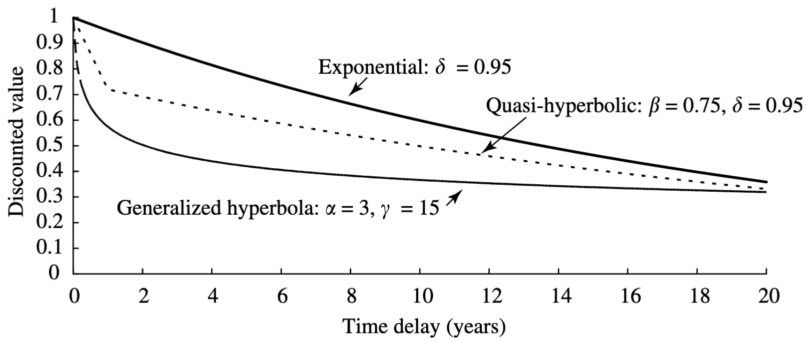

Figure 1. Exponential, hyperbolic and quasi-hyperbolic discounting functions from Chabris et al. (2010). Intertemporal choice. In *Behavioural and experimental economics* (p. 169). Palgrave Macmillan, London

3.1.5 Criticisms

The quasi-hyperbolic and hyperbolic functions including their extensions (see e.g. Myerson and Green, 1995) can both account for variance in actual discounting behavior similarly well; their value lies in their simplicity and strong descriptive validity. Nevertheless, they do not, or were at least not designed to, consider the actual psychological let alone neural mechanisms underlying intertemporal choice, which early economists already speculated about (see section 3.1.1). For instance, most studies employing these models assume linear utility functions for the rewards being discounted - an assumption at odds with empirical evidence (e.g. Galanter, 1962). More recent propositions, such as the additive-utility model (Killeen, 2009), which states that intertemporal decisions are made by subtracting the disutility of waiting from the (concave) utility of a good, have thus far failed to achieve broader acceptance.[3] A promising avenue that might lead to more comprehensive, process-related models is to examine the neural mechanisms underlying intertemporal choice, which has recently been done by neuroeconomists. The current state of this young but highly fruitful line of research, led by the overarching goal to study decision-making by combining insights from economics, psychology and neuroscience, shall be presented in the next section.

[3] A radically different viewpoint has recently been put forth by Marzilli Ericson et al. (2015), who concluded that simple heuristics (i.e. "rules of thumb") provide a better account of intertemporal choices than exponential and hyperbolic discounting. This indicates that research on modeling discounting behavior is still far from establishing a gold standard.

3.1.6 Neural basis of delay discounting

The importance of developing a better understanding of intertemporal choice, delay discounting and its underlying mechanisms has raised great interest among neuroscientists to bring their novel methods and expertise into this field of study. Since the 2000s, an increasing number of studies has investigated neural activity when humans make intertemporal choices in the lab. The majority of these experiments has been conducted using functional magnetic resonance imaging (fMRI), a non-invasive technique which takes advantage of the fact that brain activity is associated with blood flow (Logothetis et al., 2001). Rather than discussing the detailed procedures of these neuroeconomic investigations, which is out of scope of this dissertation[4], the following paragraphs shall outline the latest findings on the brain regions involved in intertemporal choices. While there is still a fair amount of disagreement on the exact neural processing of immediate and delayed rewards, researchers have come to some consensus that three networks representing reward valuation, cognitive control and prospection play a vital role in delay discounting (Peters and Büchel, 2011).

Reward valuation

Leading neuroeconomists have theorized that, for any decision, subjective values of the available options are initially formed in the human brain (Kable and Glimcher, 2009). This account includes intertemporal choices, which have been shown to activate the ventral striatum, located in the forebrain, and the orbitofrontal cortex, located above the orbits in the frontal lobe (e.g. Kable and Glimcher, 2007; Peters and Büchel, 2009). One group of researchers has posited that this valuation process takes place in two separate systems, one for immediate rewards and one for delayed rewards (McClure et al., 2004), which coincides with the quasi-hyperbolic β-δ discounting model introduced in section 3.1.4. Subsequent studies, however, did not support this hypothesis and instead suggest a single valuation system for both rewards (Kable and Glimcher, 2007; Luo et al., 2009; Sellitto et al., 2010). Independent of this ongoing debate, mounting evidence indicates that individuals showing reduced sensitivity within the neural valuation network tend to show steeper discounting (Peters and Büchel, 2011) - a finding which is particularly relevant for research on addiction, which will be described further in section 3.1.8.

[4] See Carter et al. (2010) for an interim review

Cognitive control

Once the subjective values of the decision options are computed and represented, systems related to choice comparison and selection take over (Kable and Glimcher, 2009). In case of choices with similar values, a decision conflict has been observed, which correlates with activity in the anterior cingulate cortex (Marco-Pallares et al., 2010; Pochon et al., 2008). The exact role of this part of the brain in resolving such a conflict remains unclear, however (Peters and Büchel, 2011). More clarity exists with regard to the function of the dorsolateral prefrontal cortex, which is located behind the forehead and is known to be involved in directing thoughts and actions in line with internal goals (Miller et al., 2002). Several studies were able to ascribe a causal role of this area in reducing impulsive choices; higher activation (representing the exertion of self-control) biased behavior towards the larger, delayed reward (McClure et al., 2004; Figner et al., 2010). This insight was recently supported by a study with young children, in which maturation of the connectivity between the dorsolateral prefrontal cortex and the valuation resulted in less impulsive choices (Steinbeis et al., 2016). Combined with findings on addicts, who show lower involvement of the prefrontal cortex than healthy individuals (Kalivas and Volkow, 2005; Everitt and Robbins, 2005), Peters and Büchel (2011) hypothesize that the prefrontal cortex modulates valuation signals and is able to override impulsive responses during intertemporal choice, resulting in more self-controlled behavior.

Prospection

While the role of the valuation and the cognitive control networks in temporal discounting are fairly well-established, a pivotal function of the amygdala and hippocampus, both situated within the medial temporal lobe, has recently been proposed (Peters and Büchel, 2010). Specifically, these two regions seem to enable humans to imagine future events (episodic prospection) and activation in this network correlates with less discounting (Peters and Büchel, 2010; Sasse et al., 2015). Taken together with the finding that damage to the prospection network increases discounting (Sellitto et al., 2010), Peters and Büchel (2011) propose that particularly the hippocampus plays a central role in vividly imagining delayed outcomes during intertemporal choice, thereby promoting less impulsive choices.

While these recent discoveries are intriguing without a doubt, numerous open questions remain. Especially, very little is known about how these different networks interact and to what extent the nature of this interaction can explain differences in delay discounting (Peters and Büchel, 2011). Nonetheless, one can acknowledge that examining the neurobiological underpinnings of delay discounting is a promising route that can lead not only to improved, process-related behavioral models but also to possible interventions that alter delay discounting behavior. These endeavors benefit from the neuroscientific insight that how an individual processes rewards, how strong her self-control is and how vividly she imagines future consequences are vital constituents of intertemporal choice. Yet, how stable or malleable are these individual differences, i.e. may delay discounting be considered a trait or a state variable? While the neural basis of temporal discounting suggests trait characteristics, more temporary shifts in behavior, being indicative of state influences, have also been observed. The next section will discuss this essential question in more detail.

3.1.7 Trait and state characteristic

Many features of delay discounting suggest it may be considered a trait, i.e. a lasting characteristic which describes an individual's behavior across a variety of contexts. Many researchers therefore use delay discounting and impulsivity interchangeably, although the latter encompasses further constructs, such as response inhibition or a general tendency to act without sufficient deliberation (Madden and Bickel, 2010). The following paragraphs will look at two forms of evidence, which are indicative of a trait-like character of delay discounting. Subsequently, findings will be presented which show that discounting behavior also exhibits slight fluctuations.

<u>Reliability</u>

First, people exhibit similar degrees of discounting when retested weeks (Simpson and Vuchinich, 2000), months (Ohmura et al., 2006) and even years (Kirby, 2009; Anokhin et al., 2011) after the initial assessment. Second, test-retest reliability occurs not only when participants complete identical delay discounting tasks (same-form reliability) but also when different paradigms (alternate-form reliability) are used in the experiments (Robles and Vargas, 2008; Smith and Hantula, 2008). Third, discounting behavior of one outcome, such as money, is related to that of other outcomes, such as food and drinks (Demurie et al., 2013; Estle et al., 2007), entertainment (Charlton and Fantino, 2008) or sexual outcomes (Herrmann et al., 2014; Johnson and Bruner, 2012). This type of trait influence (cross-outcome reliability) is subject to further investigation in study 3 of this dissertation. Lastly, Dixon et al. (2006) found that temporal discounting in a gambling context was strongly associated with that in a non-gambling context, which provides initial evidence of cross-context reliability.

Heritability

Further support for the trait perspective is provided by recent evidence that delay discounting is partially genetically determined. Initial studies found that differences in humans' dopaminergic system can account for a small but significant portion of variability in discounting behavior (Kringelbach and Rolls, 2004; Eisenberg et al., 2007). Subsequent twin studies concluded that up to 50% of variance in delay discounting can be attributed to genetic factors (Anokhin et al., 2011), which suggests that not just dopamine-related genes play a role in delay discounting.

While the temporal and contextual stability as well as heritability of discounting behavior indicate trait-like features, it has also been found to be malleable depending on various factors. Some of these adaptations were already mentioned in section 3.1.3; the magnitude, sign, domain or commodity and framing effects are all testament to state-dependent shifts and show that delay discounting is not perfectly fixed but can be manipulated in experiments. To further underline this malleability, the following paragraph will highlight some interventions undertaken by researchers, which are not directly related to the variables of the delay discounting task.

Clinical interventions

Morrison et al. (2014) found that people who had undergone a mindfulness program (i.e. mental training to strengthen non-judgmental awareness of present thoughts, emotions and sensations) exhibited lower discount rates than before the program. Contingency management, in which substance abusers are rewarded for verified abstinence, also seems to reduce delay discounting in clinical subjects (Weidberg et al., 2015; Yi et al., 2008). Black and Rosen (2011) concluded that a 36-week long money management intervention resulted in lower discount rates in patients with a history in cocaine and alcohol use.

Episodic future thinking

Section 3.1.6 already indicated the central role of a person's capability to project the self into the future in the context of intertemporal choice. Consequently, several studies have targeted this capability by prompting participants to vividly imagine future events prior to choosing smaller, immediate or larger, delayed rewards. Researchers found strong evidence that episodic future thinking reduces impulsive choices across a variety of populations (e.g. Peters and Büchel, 2010; Daniel et al. 2013; Kwan et al., 2015).

Other interventions

Certain cues (e.g. presentation of images of nature) have been shown to decrease delay discounting (Berry et al., 2014; Van der Wal, 2013). Similar effects have been shown for priming, for instance by evoking participants' gratitude (DeSteno et al., 2014) or by asking participants to imagine their own death (Kelley and Schmeichel, 2015). Rung and Madden (2018) present a systematic review and meta-analysis of the many experimental procedures to reduce delay discounting, which clarify that the degree of discounting, despite showing many features of a trait variable, also has a state component.

The aforementioned literature suggests that people have an individual "baseline" tendency to discount future rewards, which represents the trait component. Nonetheless, slight but significant shifts in behavior also occur to adapt to certain decision contexts, reflecting the state component of delay discounting. The next section will underline why this knowledge is highly relevant in clinical settings; researchers have established a robust link between discounting of delayed rewards and a host of maladaptive behaviors.

3.1.8 Addiction and problematic behaviors

As the hyperbolic discounting model (see section 3.1.4.) and its features became established in the 1990s, psychologists began to investigate possible links to substance abuse. They recognized the parallels in choice patterns, in that addicts opt to consume a substance which gives them immediate pleasure but negatively impacts their health, social life, finances, career and other domains in the long run (Madden et al., 1997). Furthermore, addicts often exhibit a preference reversal implicit in hyperbolic discounting; they state a preference for the larger, delayed reward (e.g. improved health) by committing e.g. not to drink or smoke in the morning but when faced with an immediate opportunity later in the day, they frequently relapse (Bickel et al., 2014). Based on this insight, researchers initially associated delay discounting with substance-based addictions. This association was later complemented with non-substance-based (or behavioral) addictions and today also extends to problematic behaviors which do not yet qualify as an addiction according to authorities such as the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM–5).

In a seminal study, Madden et al. (1997) found that opioid-dependent participants discounted money and heroin more steeply than matched non-drug-using controls. Kirby et al. (1999) replicated these results with heroin addicts, thereby introducing the 27-item Monetary Choice Questionnaire, which would become a frequently used delay discounting assessment. Similar patterns were observed in cocaine/crack addicts (e.g. Coffey et al., 2003) and in individuals consuming arguably less harmful drugs, such as alcohol (e.g. Vuchinich and Simpson, 1998) or tobacco (e.g. Mitchell, 1999). Petry (2001b) then extended these findings towards a non–substance-based (or behavioral) addiction, namely pathological gambling. Both meta-analyses of these types of studies (i.e. comparing addicts with controls) and studies examining continuous associations between delay discounting and addictive behaviors have found strong support for the findings that addicts discount more steeply than controls and that the degree of discounting is robustly related to addiction severity and consumption quantity/frequency (MacKillop et al., 2011; Amlung et al., 2017). More recently, researchers have linked delay discounting to further problematic behaviors, which are not officially classified as addictions, such as overeating (e.g. Weller et al., 2008), internet gaming (e.g. Tian et al., 2018) or compulsive buying (e.g. Nicolai and Moshagen, 2017).

The unambiguous link between delay discounting and maladaptive behaviors raises the question of the causal direction between the two variables; does steep discounting result in addictive behaviors or does consuming drugs, gambling etc. increase a person's degree of discounting? This question is not yet entirely resolved, but current evidence indicates that engaging in addictive behaviors does not alter discounting behavior (Peters and Büchel, 2011). Rather, consistent with the trait perspective on temporal discounting, more impulsive individuals (due to genetics and other factors) seem to develop these negative behaviors and are less likely to overcome them (Rung and Madden, 2018). Bickel et al. (2012) proposed that delay discounting may be considered a trans-disease process underlying substance-based and behavioral addictions as well as other impulsive behaviors. This has resulted in the development of initial clinical interventions to promote sustainably shallower discounting, i.e. to alter the trait component of delay discounting (Bickel et al., 2019).

While the outcome of such programs is eagerly awaited, in the face of rapid technological advancements and permanent societal changes it will remain critical to advance and update the “list” of maladaptive behaviors that are associated with delay discounting. On that note, at this point the reader is invited to consider how many times she checked her smartphone during the reading of this dissertation thus far. What this striking behavior might have to do with discounting of delayed rewards, is the theme of the next section.

3.2 Delay discounting and digital device use

The opening paragraphs of this dissertation acknowledged the dominant role that digital devices have come to play in our lives. Aside from bare biological necessities, it has nowadays become difficult to conceive of an activity that cannot be done in a digital fashion. This development is unlikely to slow down let alone stop considering the digitalization megatrend, which constantly introduces innovative digital products to consumers. But what does this societal shift have to do with intertemporal choice and delay discounting? In the next paragraphs, three rationales will be provided for why there may be overlap between usage of digital devices and delay discounting and why the relationship between the two concepts is a valuable field of research. In the process, the current state of the young literature on this topic shall be briefly summarized.

First, due to heavy usage and frequently observed negative consequences, particularly in younger populations, some researchers have argued for the novel diagnoses of “smartphone addiction” (e.g. Lin et al., 2016) or “digital addiction” (e.g. Hawi et al., 2019) and have developed corresponding diagnostic scales. They define addiction to these devices as excessive use with negative impact on educational, social, psychological and health outcomes (Hawi et al., 2019). However, these proposed disorders are recognized neither by the DSM-5 nor by the WHO’s eleventh revision of the International Classification of Diseases (ICD-11). In fact, Panova and Carbonell (2018) reviewed the relevant literature and concluded that the consequences of excessive digital device use do not meet the severity levels of addiction. Therefore, they suggest that observed behaviors in smartphone, tablet and laptop/PC addiction research should be labeled as problematic or maladaptive use (Panova and Carbonell, 2018). Regardless of the label, the authors acknowledge that gratification, impulse control and delayed adverse consequences are central aspects of digital technology use, which makes it an intriguing concept to investigate in the context of intertemporal choice. Initial studies found an association between excessive smartphone use and delay discounting, using either a smartphone addiction scale (Tang et al., 2017), self-reports (Wilmer and Chein, 2016) or an application installed on participants’ phones (Hadar et al., 2017) to assess usage patterns. However, these findings are subject to various measurement biases and need replication using more objective and less intrusive methods.

Second, a group of psychologists have hypothesized that intensive, prolonged engagement with digital devices may cause alterations in cognition, such as attention, memory or even temporal discounting (Wilmer et al., 2017). These concerns are based on the combination of neural plasticity in humans, i.e. the ability of the brain to be shaped by experience (Nelson, 1999), and the fact that many mobile technology users increasingly "offload" tasks such as navigation, basic calculations or memorizing facts to their smartphones, tablets or laptops/PCs. Wilmer et al. (2017) conducted a review on studies investigating the possible impact of mobile technology use on various domains of cognition. They concluded that - due to the correlational nature of most studies - there is not sufficient evidence for the claim that mobile devices alter our way of thinking, including delay discounting. The literature is lacking longitudinal studies and even more importantly research on children's and adolescents' use of digital devices. On the one hand, penetration of digital devices among the young population is reaching similar levels to adults (vom Orde and Durner, 2021). On the other hand, the plasticity of the developing brain is much higher than that of adults (Kolb and Gibb, 2011), so the aforementioned findings might not apply to children and adolescents in equal measure. Furthermore, discounting of future rewards and academic achievement in childhood are important predictors of well-being in adult life (Mischel et al., 1989), so their interdependencies with - particularly problematic - use of digital devices is warranted. To date, only one study (Tian et al., 2018) has linked one related aspect of maladaptive technology use, namely Internet Gaming Disorder, to delay discounting in adolescents. The associations between children's problematic use of digital devices overall and both temporal discounting and academic performance have yet to be investigated.

Third, the popularization of digital devices occurred nearly simultaneously with the rise of social media, such as Facebook or Instagram. These platforms, which boast a combined global user base of around 4 billion and are used the longest on digital devices (Data.ai, 2021), have introduced a novel kind of reward, namely likes and followers. Instagram users, for example, seek to maximize the amount of likes they receive on their posts and to gain followers, which represents a person's popularity on the platform. While the delay discounting phenomena described in section 3.1.3 have been shown with various reward types, no study has investigated delay discounting of social media rewards. Such research may provide important insights on why and by whom digital devices are often used excessively

3.3 Research questions

Having demonstrated various interfaces between the established concept of delay discounting and the relatively novel phenomenon of digital device use, this section will focus on formulating research questions that seek to address the previously identified gaps in the literature. Figure 2 gives a schematic overview of the relevant insights from previous research and shows where the research of this dissertation seeks to enhance existing knowledge.

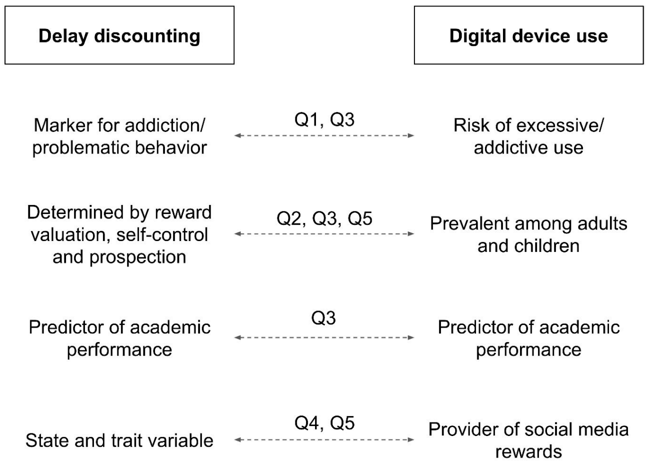

Figure 2. Research context of this dissertation

Q1: What is the relationship between delay discounting and smartphone use?

Previous studies have found that the longer a person engages with her smartphone, the more steeply she discounts monetary rewards. However, these studies have relied on subjective addiction scales, participants' estimations of smartphone engagement or usage logging applications, which were installed with participants' prior consent and thus their awareness of being observed. These kinds of measures have repeatedly been found to diverge from actual usage behavior (e.g. Ellis et al., 2019) or are subject to experimenter demand effects (Zizzo, 2010). However, a novel non-intrusive alternative has emerged, which leverages the native iOS feature "Battery usage". It passively logs the usage duration of every app installed on users' phones and thus provides an objective, granular and accurate measure of screen time (Gower and Moreno, 2018). The first research goal is to replicate past findings, employing this new, improved method to assess smartphone use.

Q2: What role do reward valuation, self-control and prospection play in the relationship between delay discounting and smartphone use?

According to a recent neuroscientific account, the subjective valuation of rewards, the ability to control thoughts, emotions and behavior as well as episodic prospection are processes that underlie delay discounting (Peters and Büchel, 2011). The second goal of this dissertation research is to investigate the role of these processes in the context of smartphone use.

Q3: What are the interrelationships between delay discounting, self-control, academic performance and addictive use[5] of digital devices in young children?

The increasing ownership of digital devices among children has led to the development of scales which seek to measure to which degree use of these devices negatively impacts educational, psychological, social and physical outcomes (e.g. Hawi et al., 2019). Examining the so far unknown relationships between addictive digital device use and delay discounting, self-control - as a central determinant of addictive behaviors (Hammond et al., 2014; Baler and Volkow, 2006) - and academic performance of young children constitutes the third research goal.

Q4: How are social media rewards discounted compared to money?

Smaller monetary and non-monetary rewards are discounted more steeply than larger rewards (magnitude effect). Furthermore, delay discounting of one outcome is associated with that of other outcomes (trait effect). The fourth research goal is to examine if these effects also occur for rewards of the social media platform Instagram, i.e. likes and followers.

Q5: What are the interrelationships between screen time, self-control and delay discounting of social media rewards?

Initial studies have indicated that screen time and self-control are related to delay discounting of monetary rewards (Tang et al., 2017; Wilmer and Chein, 2016). The last goal of this dissertation research is to replicate these findings with social media screen time specifically and delay discounting of social media rewards.

[5] As the diagnosis “digital addiction” is heavily debated (see previous section), the more conservative formulation “addictive use of digital devices” is used when referring to use of smartphones, tablets and laptops/PCs with adverse consequences.

4. Summary of dissertation studies

At the end of the previous chapter, five research questions related to various aspects of the relationship between delay discounting and use of digital devices were identified. This chapter summarizes three empirical studies conducted by the author (and his supervisor for studies 1 and 3), which sought to address these research questions. Questions Q1 and Q2 were the themes of study 1 (Schulz van Endert and Mohr, 2020), Q3 was investigated in study 2 (Schulz van Endert, 2021), whereas Q4 and Q5 were attended to in study 3 (Schulz van Endert and Mohr, 2022). The full-length articles can be found in the appendix.

4.1 Study 1: "Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting"

Smartphones have become constant companions for most people in the developed world. Not only does nearly everyone own such a device, but also are they picked up first thing in the morning, used frequently during the day - even in seemingly inappropriate places such as the bathroom - and consulted just before going to sleep (Wheelwright, 2022). Many respondents additionally admit that they check their phone during the night. Some researchers have thus argued for the novel diagnosis of smartphone addiction (e.g. Lin et al., 2016) but its potential inclusion in official diagnostic tools such as the DSM-5 is still heavily debated. Others have approached the issue by investigating psychological factors (e.g. memory, attention, risk-taking) which are associated with heavy use of smartphones. One strand of the literature, which examines possible links of smartphone use and delay discounting, i.e. the devaluation of rewards due to their delayed receipt, has produced some intriguing initial findings. Delay discounting has been proposed as the process underlying the preference for smaller, immediate rewards to larger, delayed rewards (Ainslie, 1975) and has furthermore been shown to be predictive of various problematic behaviors, such as substance abuse, gambling or overeating (Amlung et al., 2017). Wilmer and Chein (2016) found that heavier smartphone use was associated with steeper discounting and higher self-reported impulsivity as well as decreased impulse control, as exhibited in a Go/No-Go task. Tang et al. (2017) grouped participants according to their scores on the Smartphone Addiction Inventory (Lin et al., 2014) and found that high and medium users discounted more extremely than low users. Hadar et al. (2017) replicated these findings using an app to track participants' usage.

These studies, despite yielding promising initial findings, have limitations concerning the measurement of smartphone engagement. Wilmer and Chein (2016) asked participants to estimate various aspects of their smartphone usage. These self-reports have repeatedly been shown to differ significantly from actual usage patterns (e.g. Andrews et al., 2015; Ellis et al., 2019). Similarly, Tang et al. (2017) used a smartphone addiction scale, entirely based on subjective, qualitative statements (e.g. “I fail to control the impulse to use my smartphone”), as a proxy for smartphone screen time. In contrast, Hadar et al. (2017) installed a usage tracking application on participants’ phones at the start of their experiment. While this method certainly provided accurate usage data, participants’ naturalistic usage behavior might have been influenced by their awareness of being observed (experimenter demand effects). Lastly, these approaches only provided an overall measure of smartphone use without considering different kinds of usage, i.e. applications being used, thereby not being able to differentiate between e.g. five-hour use of GPS navigation and five-hour use of social media.

In this present study, in addition to self-reported screen time, we leveraged the native iOS feature “Battery usage”, which automatically tracks screen time of every app being used by the smartphone owner in the previous seven to ten days. Crucially, participants were not told that this data would be used until the start of the experiment.[6] We further assessed participants’ tendency to discount future rewards with the 27-item Monetary Choice Questionnaire (Kirby et al., 1999) employing hypothetical rewards ranging from 11 Euro to 185 Euro. Based on Peters and Büchel’s (2011) recent neuroscientific account, which proposes reward valuation, cognitive control and episodic prospection as processes underlying temporal discounting, we also elicited the following variables: 1) reward responsiveness using the BIS/BAS scale (Carver and White, 1994), 2) self-control using the Brief Self-Control Scale (Tangney et al., 2004) and 3) the extent to which distant vs. immediate consequences of potential behaviors are considered using the consideration of future consequences scale

[6] Data was only obtained only with written consent, which was given by about 95% of participants.

(Strathman et al., 1994). Additionally, we assessed response inhibition by means of a Go/No-Go task. We collected data from 101 university students recruited through the volunteer database of the Berlin Social Science Center (WZB).

First, we found a negative correlation between overall screen time and the proportion of choices for the larger, delayed reward (LDR) as an atheoretical measure of delay discounting. This relationship was still present after conducting a regression analysis which included demographic and psychological variables as independent variables. The more time was spent engaging with a smartphone, the less the larger, delayed reward was chosen, representing steeper discounting.

Second, to determine the drivers of the previously found relationship we conducted another regression analysis with screen time broken down by application categories as well as demographic and psychological variables as predictors of delay discounting. We found that screen time of social media and gaming apps were the only significant predictors of the LDR proportion.

Third, from the psychological variables[7] according to Peters and Büchel (2011) self-control was negatively associated with screen time, whereas response inhibition and consideration of future consequences were not. We then performed three mediation analyses using the PROCESS model (Hayes, 2012) to analyze whether self-control, response inhibition or consideration of future consequences mediated the relationship between screen time and delay discounting. We found that neither variable played a mediating role in the relationship between screen time and delay discounting.

Fourth, actual screen time was moderately associated with self-reported screen time. 71% of participants overestimated and 17% underestimated their screen time. For only 12% of participants, actual screen time fell into their estimated usage interval (e.g. “2.5 to 3 hours per day on average”).

[7] As the internal consistency of the reward responsiveness measure was low we excluded this variable from data analyses.

4.2 Study 2: “Addictive use of digital devices in young children: Associations with delay discounting, self-control and academic performance”

The use of smartphones is ubiquitous, not only among adults but also among children and adolescents. In 2019, approximately two thirds of 5- to 16-year-olds in developed countries owned a smartphone and spent an average of 3.4 hours online, mostly watching videos, using social media or playing games (Childwise, 2020). The COVID-19 pandemic has then led to an additional drastic increase (e.g. +163% in Germany) in screen time due to closing of schools and restrictions on personal meetings (Schmidt et al., 2020). This development has fueled the debate about the addiction potential of digital devices (smartphones, tablets and laptops/PCs) as research accumulates demonstrating adverse effects of excessive use, such as lower sleep quality and quantity (Thomée et al., 2011), heightened stress (e.g. Chiu, 2014) or worse academic achievement (e.g. Hawi and Samaha, 2016). While the label of addiction might be too extreme (Panova and Carbonell, 2018), diagnostic scales that assess the degree of digital device use with negative consequences may nonetheless be useful to develop a better understanding of the prevalence of such problematic use, which enables possible future interventions. One such scale aimed at young children, who are particularly at risk of developing addictive behaviors (Spear, 2000), has recently been introduced by Hawi et al. (2019).

In this present study, we investigated children’s addictive use of digital devices and its links to delay discounting (as a reliable indicator for various problematic behaviors), self-control (as a key determinant of the development and overcoming of addictive behaviors) as well as academic performance (as a central ingredient for future well-being). Previous studies investigated older samples and focused on single aspects of digital device use, such as Internet gaming (Tian et al., 2018) or smartphone screen time (Schulz van Endert and Mohr, 2020). We collected data from 72 students aged 10 to 13 of an elementary school in Berlin, Germany. This age span is of high importance for the educational trajectory of students in Berlin, as they will progress to one of two different types of schools (“Gymnasium” or “Integrierte Sekundarschule”) depending on their academic performance. The degree of digital device use negatively affecting social, psychological, physical and educational outcomes was measured with the 25-item Digital Addiction Scale for Children (Hawi et al., 2019). Delay discounting was assessed using Kirby et al.'s (1999) Monetary Choice Questionnaire, which is an efficient instrument also suitable for children. The Brief-Self Control Scale (Tangney et al., 2004) was employed to assess children's ability to regulate thoughts, emotions and behavior. The recent semester's grade average served as an indicator for academic performance. We also elicited self-estimations of screen time and several control variables.

We found that addictive use of digital devices was positively related to delay discounting, controlling for demographic variables. The more often children chose the smaller, immediate reward, the higher they scored on the Digital Addiction Scale. Self-reported screen time was also related to addictive digital device use but not to delay discounting.

Next, there was a strong negative relationship between self-control and scores on the Digital Addiction Scale, while self-control was also related to delay discounting, suggesting a possible confounding role of self-control. Indeed, when self-control was included as an independent variable in a multiple regression model, delay discounting no longer significantly predicted addictive use of digital devices. Instead, self-control and self-reported usage duration were significant predictors of scores on the Digital Addiction Scale.

Lastly, we found that addictive use of digital devices was not associated with academic performance. However, self-reported screen time and self-control predicted children's recent grade average. On the one hand, the longer children reported to use digital devices, the worse their grades were. On the other hand, the better they were able to control their thoughts, emotions and behavior the better their accomplishments in the classroom were.

4.3 Study 3: “Delay discounting of monetary and social media rewards: magnitude and trait effects”

Delay discounting, i.e. the tendency to discount rewards as a function of the delay to their receipt, has been extensively researched in the last decades. Several phenomena have been observed in the literature. One of these is the magnitude effect, i.e. smaller rewards are discounted more steeply than larger rewards (e.g. Thaler, 1981). This behavior is at odds with economic theory, which posits a single discount rate for intertemporal choices if the implied rate of return is identical (Samuelson, 1937). A prominent explanation for the magnitude effect is that a decision-maker’s value function is convex for smaller rewards but becomes more elastic for larger rewards (Loewenstein and Prelec, 1992). Thus, the difference between e.g. USD5 today and USD10 in one year is perceived as smaller than e.g. USD50 and USD100 in one year, even though both choices imply the same rate of return. Another robust finding is the trait effect, i.e., delay discounting of one reward type is predictive of delay discounting of other reward types. Individuals exhibit slightly different discount rates for e.g. money and for consumable rewards but the discount rates are correlated (Odum et al., 2020). This phenomenon has been attributed to the trait-like character of delay discounting - a perspective supported by recent evidence from genetic studies showing a partial heritability of delay discounting behavior (Anokhin et al., 2011; Wilhelm and Mitchell, 2009). Both the magnitude and the trait effect have been shown in the context of different reward types, such as money (e.g. Green et al., 1997), food and drinks (e.g. Jimura et al., 2009) and entertainment (e.g. Friedel et al., 2014).

Here, we wanted to investigate if these effects also occur when people discount the novel reward types of Instagram followers and likes. Instagram is an immensely popular social media platform, where users receive feedback on their posted content from other users in the form of likes and additional followers. The numbers of likes and followers have become highly demanded metrics, which is manifested by the formation of businesses that sell fake, computer-generated likes and followers. Additionally, previous studies have shown that self-control and screen time are related to delay discounting of monetary rewards (e.g. Schulz van Endert and Mohr, 2020; Schulz van Endert, 2021). In this present study, we examined if these findings can be replicated in the context of social media rewards. Therefore, we conducted a within-subject online experiment with 214 Instagram users recruited from the online participant pool Prolific. Participants chose between smaller, immediate and larger, delayed amounts of hypothetical money, Instagram followers and likes within the Monetary Choice Questionnaire (Kirby et al., 1999). For Instagram rewards, only the reward type was changed while the amounts and delays remained identical. Self-control was assessed with the Brief Self-Control Scale (Tangney et al., 2004). Participants also provided estimations of their average daily use of the Instagram app, their goals and attitudes towards Instagram use as well as several control variables.

First, we found that the magnitude effect not only occurred for monetary rewards but also for Instagram followers and likes. Small rewards were discounted more steeply than medium rewards and medium rewards were discounted more steeply than large rewards for all three reward types.

Second, delay discounting of all three reward types was correlated. Delay discounting of followers and of likes showed the strongest correlation, followed by delay discounting of likes and of money. The relationship between delay discounting of money and of followers was the weakest but nonetheless significant. Looking at the delay discounting sub-measures (i.e. broken down by reward size), we found that correlations were not the highest for matched reward sizes (e.g. small money vs. small followers, medium likes vs. medium followers). No clear patterns emerged when relating Instagram goals and attitudes to discounting behavior.

Third, no relationships were found between any of the three delay discounting measures and self-control as well as Instagram screen time, respectively. However, a user’s average like count was positively related to delay discounting of Instagram likes, after controlling for psychological and demographic variables.

5. Discussion

The previous chapter summarized three empirical studies which addressed the five research questions developed in chapter 3. In the following, I will return to these questions one by one and discuss to what extent the study findings have answered them. Subsequently, a general discussion reflecting on the overall gain in knowledge will be presented along with an outlook onto future research on the relationship between digital device use and delay discounting. This dissertation will end with a brief conclusion, referring back to the opening paragraphs.

5.1 Discussion of research questions

Q1: What is the relationship between delay discounting and smartphone use?

In study 1, we found a positive relationship between actual smartphone usage and the discounting of future rewards. This result is in line with previous studies investigating the association between delay discounting and smartphone usage primarily based on self-reports (Wilmer and Chein, 2016; Tang et al. 2017; Hadar et al. 2017). Taken together, a behavioral pattern has emerged in these few existing studies: as smartphone screen time increases, the tendency to prefer smaller immediate to larger delayed monetary rewards increases as well. Additionally, the high percentage of inaccurate estimations of screen time in our study corroborates the use of actual data instead of self-reports, which has now been proposed by a number of studies (see Ellis, 2019).

We also identified two application categories, namely social media and gaming, as drivers of the relationship between delay discounting and smartphone use. This result seems intuitive from both a statistical as well as a conceptual perspective; both types of apps typically constitute the majority of screen time and are characterized by swift gratification (e.g. social feedback and entertaining content on social media and rewards or bonuses while gaming). This interpretation is supported by recent research showing that behavior on social media conforms to the principles of reward learning (Lindström et al., 2021). However, it needs to be acknowledged that other smartphone applications (e.g. shopping) may also involve strong gratification and share similar mechanisms by sending notifications and quickly providing information. Thus, analyzing the reward mechanisms of different smartphone applications appears to be an important topic for future research.

Two caveats need to be taken into account when looking at these results. First, while the observed relationships between smartphone use and delay discounting are significant, the effect sizes throughout existing studies appear to be small ($r < 0.3$). This might be either due to the actually weak association between the two variables in the population or due to limitations of measurement. For instance, the “Battery usage” feature used in our study only logged usage data of the previous seven to ten days. As this timeframe might not always reflect people’s typical usage patterns, future studies should leverage longer logging periods that are available on newer phones (e.g. iPhones released since 2020 yield screen time data of the four previous weeks). Also, the Monetary Choice Questionnaire is a very efficient yet less sensitive instrument compared to more extensive or adjusting-amount procedures (see section 3.1.2). Second, due to the correlational design of this study we cannot draw inferences on causality. Thus, excessive smartphone usage may cause an individual to choose more impulsively over time. However, it is also possible that individual differences in the degree of discounting result in longer engagement with smartphones. This central issue will be explored further in the general discussion.

Q2: What role do reward valuation, self-control and prospection play in the relationship between delay discounting and smartphone usage?

Three neural processes have been proposed as underlying mechanisms of delay discounting (Peters and Büchel, 2011). In study 1, we found that self-control (assessed with the brief self-control scale) was unrelated to delay discounting but negatively related to screen time; people who used their phones excessively also exhibited lower self-control than those who spent less time with their phones. The lack of an association between self-control and delay discounting is at odds with previous findings as these variables are typically closely related (Duckworth and Kern, 2011). The second process of prospection was operationalized as the inclination to consider distant vs. immediate consequences of behavior and was surprisingly neither associated with screen time nor with delay discounting. This suggests that consideration of future consequences and delay discounting may not be used interchangeably in the context of smartphone use, despite their conceptual overlap.

Concerning the third process, in our study we could not make inferences on reward valuation as the elicited variable was not included in data analyses. Furthermore, we found that neither self-control, nor response inhibition nor consideration of future consequences were mediators of the relationship between smartphone screen time and delay discounting. Under the assumption of a causal process, this may indicate that smartphone usage has a direct influence on delay discounting and that self-control, response inhibition and consideration of future consequences are not mechanisms underlying the relationship between screen time and delay discounting. However, this preliminary conclusion needs further investigation for several reasons. First, a causal relationship has yet to be established between the two main variables of interest in order to make inferences on possible mediators. Our study design precluded any such analyses of causality. Second, instead of neuroscientific methods, through which the investigated model of delay discounting has emerged, we employed questionnaire-based instruments to assess the three psychological variables in this current study. These constructs may not have sufficient overlap with the neural processes suggested by Peters and Büchel (2011). Lastly, the role of individuals' valuation of rewards has yet to be investigated.

Q3: What are the interrelationships between delay discounting, self-control, academic performance and addictive use of digital devices in young children?

Previous studies have consistently linked delay discounting to addictive behaviors, e.g. drug and tobacco use, problematic drinking, gambling (Amlung et al., 2016). In study 2, delay discounting was also associated with children's addictive use of digital devices; children who discounted future rewards more extremely tended to report stronger negative social, psychological, physical and educational consequences due to digital device use. At the same time, it seems that shallow discounters are less attracted to the immediate rewards of playing games, watching videos or messaging and thus experience negative outcomes of digital device use less frequently. Even though the direction of causality is unclear, delay discounting may at least serve as an indicator for addictive use of digital devices - comparable to other problematic behaviors. While this pattern was previously only observed in older samples (Amlung et al., 2016), the results in study 2 indicate that adverse outcomes due to smartphone, tablet and laptop/PC use can already occur in childhood. However, the low correlation between self-reported screen time and addictive use suggests that the two concepts may not be equated; not all children seem to experience negative outcomes with increased usage.

Further clues about the nature of the relationship between delay discounting and addictive use of digital devices are given by the role of self-control in study 2. Self-control was a confounder of the relationship between the two variables, which implies that steeper discounters showed greater degrees of addictive digital device use due to lower self-control. Thus, children's ability to control their thoughts, behavior and emotions appears to be a better predictor of problematic engagement with smartphones, tablets and laptops/PCs, which is also manifested by the high correlation between the two variables. A possible mediating role of self-control, which was shown in a previous study investigating smartphone use and delay discounting (Wilmer and Chein, 2016), cannot be ruled out. A mediation analysis in future research would require established causal relationships between the variables of interest. Nonetheless, given previous findings that self-control training reduces the risk of addiction (Tang et al., 2015; Yeun and Han, 2016; McClure and Bickel, 2014), self-controlled children are likely better able to resist the temptation of continued gaming, watching videos or chatting, thereby preventing harmful consequences. In contrast, children who are less able to control themselves as a result have more conflicts with family and friends, show withdrawal symptoms, experience mood swings etc. due to their use of digital devices.

Finally, intriguing association patterns emerged in the context of children's academic performance. Contrary to previous findings with other problematic behaviors (e.g. Akhter, 2013; Aertgeerts and Buntinx, 2002), no significant association was found between addictive use of digital devices and academic performance in study 2. Instead, the more time children reported to spend with smartphones, tablets and laptops/PCs the less they succeeded in the classroom. On the one hand, this suggests that despite experiencing negative social, psychological and physical outcomes due to digital device use children may still receive good grades. On the other hand, screen time seems to take away study time which results in worse academic performance, which is supported by a recent study showing a negative impact of smartphone use on exam scores (e.g. Baert et al., 2020). Lastly, in study 2 self-control predicted students' recent semester grade average, which is consistent with the literature on the role of self-control in academic achievement (Duckworth et al., 2019). The main limitations of this study are the small sample size and the use of self-reports for the main variables. Our findings thus need replication using larger, more diverse samples while also incorporating reports from parents/guardians and educators. In sum, our findings provide additional support to the notion of developing children's self-control both to prevent addictive behaviors and to promote academic success.

Q4: How are social media rewards discounted compared to money?

Numerous delay discounting studies have been conducted with monetary and non-monetary rewards and have consistently shown a magnitude (see section 3.1.3) as well as a trait effect (see section 3.1.7). In study 3, our main goal was to extend this literature by examining if these effects also apply to rewards of the widespread social media platform Instagram. First, we found strong support for a magnitude effect; delay discounting decreased with increasing reward magnitude for money, Instagram followers and Instagram likes. Loewenstein and Prelec (1992) have provided the most widely accepted explanation of this effect; the curvature of the decision-maker's value function changes with increasing reward size from being initially convex to straightening out eventually. This implies that intertemporal choices involving equivalent ratios (e.g. USD5 today vs. USD10 in one year and US50 today vs. USD100 in one year) are nonetheless subjectively valued differently; in the latter, people perceive a larger value gain so they choose the larger, delayed reward more often. Our results suggest that when discounting the novel, social reward types of Instagram followers and likes the shape of the value function underlying people's choices is not fundamentally different from that for other reward types.

Second, our data showed a pronounced trait effect of delay discounting; delay discounting of money, followers and likes was correlated, which has previously been found for various other rewards (Odum et al., 2020). On average, shallow discounters of money also discounted social media rewards less extremely, reflecting the trait-character of temporal discounting. Shared variation was largest between delay discounting of Instagram followers and likes, which comes as no surprise as both are social rewards from the same platform. However, the result that money and follower discounting had less shared variance than money and like discounting is somewhat counterintuitive. The number of likes a user receives is most relevant when content is posted and fluctuates considerably depending on the nature and timing of the post. Additional Instagram followers, in contrast, are received less frequently and in much lower numbers and are displayed like an account balance on the platform, thus seeming more comparable to money than likes are. Possibly, the answer lies in the value functions of the three reward types as the breakdown of delay discounting by magnitude revealed that the three reward types were not of equal subjective value.

A related question, that could not be answered in this study, was if social media rewards are discounted more or less steeply than money. Delay discounting of non-monetary rewards is typically higher than that of monetary rewards (Odum et al, 2020), but investigations of this phenomenon require that reward magnitudes are scaled to equal monetary or subjective value. We did not calibrate reward magnitudes, so the observed differences in delay discounting between reward types may simply be due to different value functions for money, followers and likes (see Chapman, 1996). Furthermore, in this present study we focused on delay discounting of rewards of the Instagram platform by their respective users. Our results thus need replication in terms of rewards of other social media platforms (e.g. Facebook), which are also characterized by different user demographics.

Q5: What are the interrelationships between screen time, self-control and delay discounting of social media rewards?

In study 3, we found that neither Instagram screen time nor self-control were related to delay discounting of any of the three reward types. Two factors may have contributed to the unexpected null finding with regard to screen time. First, Schulz van Endert and Mohr (2020), who found that screen time predicted delay discounting, included screen times of other smartphone applications (e.g. games, shopping, other social media). Second, in study 3 we elicited self-reported duration of Instagram use, which bears a risk of insufficient accuracy compared to measurement based on applications (Ohme et al., 2021). With regard to self-control, we hypothesize that the null finding may also partly be due to measurement, as the elicited variable was not associated with delay discounting in study 1 either, which also employed the Brief Self-Control Scale. Self-control is robustly linked with delay discounting, but the construct has multiple facets and can be elicited in different ways (Duckworth and Kern, 2011). Future studies may employ other, more extensive instruments, such as the Barratt

Impulsiveness Scale (Patton et al., 1995), or behavioral measures, such as response inhibition tasks.

People's goals and attitudes towards the Instagram platform, based on our brief elicitation method, did not provide any clues about their delay discounting behavior. However, we found that the more likes a person typically receives for their content, the more often they choose the smaller, immediate amount of likes. A plausible explanation for this result emerges when taking into account two factors. First, "popular" users, who receive plenty of likes, also tended to state that they wished to maximize their follower and like count. Second, the Instagram algorithm displays content which quickly receives positive social feedback more prominently. Thus, popular users seem to give greater priority to an immediate delivery of likes so as to increase visibility which in turn increases the chance of attaining their goal of a high number of likes. Contrariwise, users who receive few likes on average seemingly place less emphasis on achieving maximum visibility and popularity and therefore tend to tolerate delays in like delivery to a greater extent.

In this section, the results of the three dissertation studies were discussed guided by the research questions. Given the insights from this rather specific discussion, the next section will focus on drawing a broader picture of the relationship between delay discounting and use of digital devices and the implications it may have for both future research and everyday life.

5.2 General discussion

Digital device use as an impulsive choice

The young literature on the relationship between delay discounting and use of digital devices, to which the research of this dissertation has contributed, indicates that there is overlap between smartphone, tablet and laptop/PC use and the tendency to choose impulsively (Tang et al., 2017; Wilmer and Chein, 2016; Hadar et al., 2017; Wilmer et al., 2019). The choice to continuously engage with a digital device, thereby sacrificing other activities and experiences, shares some characteristics with the choice to forgo larger rewards with a delay for smaller rewards which are available immediately. The empirical investigations confirm the intuition that checking social media, playing games, shopping online or browsing the news, which are all conveniently and swiftly available in people's pockets, are rewarding activities which come at the expense of better outcomes in the future to a certain extent. However, the observed small effect sizes throughout studies suggest that this overlap is limited; impulsive decision-makers may often be low users of digital devices, while less impulsive people may well have difficulty putting their devices aside. Why is this the case?

Digital devices can nowadays be used for a plethora of purposes; this includes productive (e.g. banking, working on documents, learning) as well as leisure activities, which are - presumably - more rewarding. In study 1, we showed that not all applications on participants' smartphones predicted delay discounting, but that screen time of two application categories (social media and gaming) were the drivers of the relationship between smartphone use and delay discounting. Similarly, David et al. (2018) found that only some apps were negatively related to subjective well-being, while other apps were even positively related to their variable of interest. Thus, overall screen time, which has predominantly been used in research so far, appears to be too coarse of a measure, which may contribute to noise in the data. Also, the majority of studies have investigated usage of a single digital device (primarily smartphones), despite the fact that many applications are nowadays used seamlessly between devices (e.g. WhatsApp on both smartphone and laptop). An additional layer of complexity is given by the fact that applications traditionally known to exist purely for entertainment purposes (e.g. YouTube, Instagram) may also be used for information, education and work. Nonetheless, future research will certainly benefit from adopting a more nuanced view on digital device use, by accounting for people's engagement with multiple devices and by breaking down screen time e.g. into application categories. Furthermore, analyses of the different reward mechanisms of applications will be highly useful in this regard.

A second reason why digital device use seems to be a "mildly" impulsive choice is conceptual in nature. For this, one needs to take a closer look at the respective intertemporal choice parameters, i.e. the stakes and the delays, and compare them to other, more established impulsive choices. The decision to engage with digital devices undoubtedly provides gratification but most likely to a lesser extent than e.g. the consumption of drugs or gambling. Analogously, Panova and Carbonell (2018) have demonstrated that the long-term consequences of excessive digital device use (e.g. impaired sleep) are less grave than those of substance abuse (e.g. severely and sustainably deteriorated health) or pathological gambling (e.g. financial ruin). Additionally, it may be argued that there is a significant difference in delay to these outcomes. While heavy smartphone users may experience heightened stress, headaches or fatigue rather soon, smokers, for instance, encounter effects, such as shortened breath or development of lung cancer, only months or even years later (Yanbaeva et al., 2007). Taken together, these considerations go hand in hand with the perspective that excessive digital device use does not qualify as an addiction due to the lower severity levels of its consequences (Panova and Carbonell, 2018).

<u>Digital device use in young children and the role of self-control</u>

Despite this preliminary conclusion, it would be a mistake to underestimate the possible negative implications of digital device use, particularly for young children. The vast majority of studies investigating people's engagement with smartphones, tablets and laptops/PCs have used university student or adult samples (Wilmer et al., 2017), in spite of a large percentage of young children already owning such devices. Given that a significant portion of cognitive development takes place during childhood (Siegler, 1994), more attention should be placed on this cohort in future research.

The results of study 2 demonstrated that children as young as ten years old may already show addiction-like symptoms, such as tolerance (i.e. feeling the need to spend increasing time with digital devices), withdrawal (i.e. feeling disoriented when not using digital devices), mood modification (i.e. using digital devices to improve mood) or displacement (i.e. preferring to engage with digital devices instead of friends, family or hobbies). However, the present data showed yet again that more screen time does not always imply problematic use (Ellis, 2019). Other factors, such as content and timing of usage, seem to play an important role in this context. The present findings indicate that children's self-control, i.e. their ability to align behavior with set goals in the face of temptations, may be a protective factor against the harmful consequences of digital device use. Importantly, while delay discounting may again serve merely as an indicator for addictive use of digital devices, self-control seems to causally influence the latter given previous findings on the role of self-control in addictive behaviors (Tang et al., 2015; Yeun and Han, 2016; McClure and Bickel, 2014). Self-controlled children seem to be able to stop using their devices at the right moments in order to engage in other activities, such as studying, spending time with friends and family or pursuing hobbies. Possibly, children high in self-control also use relatively more of their screen time for educational purposes, as their academic performance tends to be higher than that of less self-controlled students. In sum, this present research contributed to the view that developing children's self-control is conducive to academic success (Duckworth et al., 2019), to the prevention of problematic behaviors (Tangney et al., 2004) and to overall well-being in the digital age (Hofmann et al., 2016).

<u>The elephant in the room: Causality</u>

Having touched on possible detrimental effects of digital device use on health as well as social and psychological well-being, it is no longer possible to dodge the question if use of smartphones, tablets and laptops/PCs also affects delay discounting or if impulsivity determines the extent of digital device use. To address this question, I will initially take a narrow, data-oriented stance; what can be firmly concluded from the existing literature? Subsequently, a broader view will be taken, thereby incorporating findings from adjacent fields in order to draw a preliminary conclusion.

The first two studies of this dissertation research, which found statistical relationships between the variables of interest, were observational and cross-sectional in nature. In the absence of theory that proposes causal relationships in this context, this design does not allow any conclusion about whether excessive digital device use makes a person more impulsive over time or if an impulsive person tends to engage longer with their smartphones, tablets and laptops/PCs (Pearl, 2009). In fact, this applies to the vast majority of not only related studies but also to research examining the relationships between digital device use and human cognition in general (Wilmer et al., 2017). The main reason for this imbalance is the practical challenge of conducting experiments in which usage of digital technologies is manipulated. As smartphones, tablets and laptops/PCs have become so ingrained in people’s lives, it is virtually impossible to find participants who are willing and able to have their usage strictly prescribed by experimenters. Concurrently, due to comprehensive adoption of digital technologies, there are barely any persons left who have not been exposed to smartphones etc. Studying these individuals, presumably being older or technology-averse, may be subject to sample bias. Nonetheless, Hadar et al. (2017) took such an approach to examine a possible causal link between smartphone usage and changes in delay discounting, numerical processing and social cognition. They gave a group of 12 smartphone non-users a device for a period of three months and compared outcomes to 16 non-users who didn’t receive a device. While observing decreased numerical processing capacity and changes in social cognition, the authors could not find any differences in the degree of discounting between the two groups. Future, larger studies may randomly allocate participants into high, medium and low user groups, each with a capped screen time interval (e.g. zero to one hour per day in the low group). Delay discounting would be measured before the intervention as a baseline and e.g. one year later[8] and then compared between groups. This design has the disadvantage of no control group, as presumably no unbiased participant would be willing to completely refrain from using any digital device over such a period. However, this would at least partly be compensated by enabling the identification of a possible dose-response relationship, which would be informative for increasingly demanded recommendations on the appropriate amount of screen time for adults and children alike.

Meanwhile, turning the gaze towards research on addiction and delay discounting, a much more mature field, may provide additional clues about the direction of causality. As already described in section 3.1.8, current evidence indicates that even prolonged

[8] Previous interventions to reduce delay discounting have shown effects within a one-year timeframe (see section 3.1.7).

consumption of addictive substances (e.g. nicotine) does not increase or decrease the degree of discounting (Peters and Büchel, 2011). Rather, impulsivity seems to promote seeking immediate pleasure and engaging in swiftly rewarding activities, thereby largely discounting future consequences of that behavior. This perspective is backed by the literature on the trait-like character of delay discounting, which has repeatedly shown a temporal and contextual stability in behavior, at least partially due to genetic factors (Odum et al., 2020). Given these various pieces of evidence, it currently seems that excessive engagement with digital devices is a consequence of being an impulsive decision-maker, who is attracted by the conveniently and quickly available gratifications digital devices have to offer. Nevertheless, the above paragraphs have implied that definite conclusions about the direction of causality cannot be taken at this stage. What the literature is also missing are longitudinal studies observing digital device use and decision-making, preferably coupled with neuroscientific variables, over long periods of time, to study behavioral and neural changes and if any effects on the observed parameters are lasting. Last but not least, more attention should be given to children's behavior in the context of digital devices as their traits, including impulsivity, are not fixed but are still shaped significantly by external influences (Roberts et al., 2005).

Digital social rewards

Any discussion of an excessive behavior that shares characteristics with impulsive choice would be incomplete without considering the rewards associated with that behavior. Based on reinforcement learning (Skinner, 1965), frequent and prolonged behavior as observed in use of digital devices, may at least be partially ascribed to reinforcements. The multitude of possible uses of digital devices imply many different types of reinforcements, which could constitute a body of research on its own. Within this dissertation research, the focus was guided by applications which have been shown to make up the majority of users' screen time. Study 1 confirmed previous studies and popular surveys that social media apps, such as Facebook, Instagram, Twitter or Snapchat, are most popular among smartphone users (e.g. David et al., 2018). More importantly, we found that usage of these apps is associated with discounting of future rewards. The question of what is so rewarding about these platforms arose.

The most obvious reward associated with social media is the positive feedback received from fellow users on content posted on these platforms, which is to a large extent expressed by likes (Fareri and Delgado, 2014). While users may also verbally communicate their reactions through comments or messages, the like button is the quickest and most convenient way to endorse content throughout most social media. Since its introduction in the 2000s, the number of likes content receives has become a central metric for people and businesses that are active in the digital sphere. Consistent with psychological accounts, recent neuroscientific evidence highlights the activation of reward-related brain regions associated with both giving and receiving likes (Meshi et al., 2015; Sherman et al., 2016; Sherman et al., 2018). Study 3 was thus an initial investigation that combined the study of discounting of delayed rewards with a central aspect of digital device use, namely social media rewards. We were able to replicate the magnitude effect of delay discounting in the context of Instagram followers and likes, which had solely been shown with “non-digital” rewards before (e.g. Thaler, 1981; Green et al., 1994; Kirby and Maraković, 1995). This implies that discounting of these novel social rewards is subject to a value function with a similar curvature than that implied in discounting of monetary or other previously researched outcomes. Furthermore, we provided further evidence of the trait-like character of delay discounting (Odum, 2011b) by showing that the degrees of discounting of money, followers and likes were all correlated. Thus, studying delay discounting in the context of social media rewards appears to be a promising avenue for further research as many of the phenomena previously observed in intertemporal choice studies now have a new field of application within the digital world.

5.3 Conclusion

We have reached the end of this dissertation and I plead guilty to having scrolled countless times through my social media feeds while writing this document. Given that I used a laptop for it, my screen time most likely qualifies as excessive by most standards. However, one of the key insights of this research is that not all digital device use is created equal; taking advantage of the many productive resources digital technologies offer while cultivating self-control seems to have limited negative consequences. People high in impulsivity are at a somewhat higher risk of being glued to their devices, which will oftentimes manifest itself in long screen time of applications with distinct reward mechanisms. Shallow discounters currently have little reason to expect that usage of digital devices will make them more impulsive. Nonetheless, digital technologies may affect other important physiological and psychological factors, such as motor skills, attention or social capabilities, particularly in children and adolescents, which were not in scope of this dissertation research. Since the results of ongoing longitudinal studies on the long-term effects of digital device use will only become available in several years, parents, guardians and educators are advised to be vigilant about children's use of existing and upcoming digital technologies.

6. References

1. Adelantado-Renau, M., Moliner-Urdiales, D., Cavero-Redondo, I., Beltran-Valls, M. R., Martínez-Vizcaíno, V., & Álvarez-Bueno, C. (2019). Association between screen media use and academic performance among children and adolescents: a systematic review and meta-analysis. *JAMA pediatrics*, *173*(11), 1058-1067.
2. Aertgeerts, B., & Buntinx, F. (2002). The relation between alcohol abuse or dependence and academic performance in first-year college students. *Journal of adolescent health*, *31*(3), 223-225.
3. Ahlbrecht, M., & Weber, M. (1997). An empirical study on intertemporal decision making under risk. *Management Science*, *43*(6), 813-826.
4. Ainslie, G. (1975). Specious reward: a behavioral theory of impulsiveness and impulse control. *Psychological bulletin*, *82*(4), 463.
5. Akhter, N. (2013). Relationship between internet addiction and academic performance among university undergraduates. *Educational Research and Reviews*, *8*(19), 1793-1796.
6. Alessi, S. M., & Petry, N. M. (2003). Pathological gambling severity is associated with impulsivity in a delay discounting procedure. *Behavioural processes*, *64*(3), 345-354.
7. Amlung, M., Vedelago, L., Acker, J., Balodis, I., & MacKillop, J. (2017). Steep delay discounting and addictive behavior: A meta-analysis of continuous associations. *Addiction*, *112*(1), 51-62.
8. Andrews, S., Ellis, D. A., Shaw, H., & Piwek, L. (2015). Beyond self-report: Tools to compare estimated and real-world smartphone use. *PloS one*, *10*(10), e0139004.
9. Anokhin, A. P., Golosheykin, S., Grant, J. D., & Heath, A. C. (2011). Heritability of delay discounting in adolescence: a longitudinal twin study. *Behavior genetics*, *41*(2), 175-183.
10. Ariely, D., & Carmon, Z. (2000). Gestalt characteristics of experiences: The defining features of summarized events. *Journal of Behavioral Decision Making*, *13*(2), 191-201.

11. Baert, S., Vujić, S., Amez, S., Claeskens, M., Daman, T., Maeckelberghe, A., ... & De Marez, L. (2020). Smartphone use and academic performance: correlation or causal relationship?. *Kyklos*, *73*(1), 22-46.
12. Baker, F., Johnson, M. W., & Bickel, W. K. (2003). Delay discounting in current and never-before cigarette smokers: similarities and differences across commodity, sign, and magnitude. *Journal of abnormal psychology*, *112*(3), 382.
13. Baler, R. D., & Volkow, N. D. (2006). Drug addiction: the neurobiology of disrupted self-control. *Trends in molecular medicine*, *12*(12), 559-566.
14. Benzion, U., Rapoport, A., & Yagil, J. (1989). Discount rates inferred from decisions: An experimental study. *Management science*, *35*(3), 270-284.
15. Berry, M. S., Sweeney, M. M., Morath, J., Odum, A. L., & Jordan, K. E. (2014). The nature of impulsivity: Visual exposure to natural environments decreases impulsive decision-making in a delay discounting task. *PLoS One*, *9*(5), e97915.
16. Bickel, W. K., Athamneh, L. N., Basso, J. C., Mellis, A. M., DeHart, W. B., Craft, W. H., & Pope, D. (2019). Excessive discounting of delayed reinforcers as a trans-disease process: Update on the state of the science. *Current Opinion in Psychology*, *30*, 59-64.
17. Bickel, W. K., Jarmolowicz, D. P., Mueller, E. T., Koffarnus, M. N., & Gatchalian, K. M. (2012). Excessive discounting of delayed reinforcers as a trans-disease process contributing to addiction and other disease-related vulnerabilities: emerging evidence. *Pharmacology & therapeutics*, *134*(3), 287-297.
18. Bickel, W. K., Johnson, M. W., Koffarnus, M. N., MacKillop, J., & Murphy, J. G. (2014). The behavioral economics of substance use disorders: reinforcement pathologies and their repair. *Annual review of clinical psychology*, *10*, 641-677.
19. Bickel, W. K., Odum, A. L., & Madden, G. J. (1999). Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. *Psychopharmacology*, *146*(4), 447-454.
20. Black, A. C., & Rosen, M. I. (2011). A money management-based substance use treatment increases valuation of future rewards. *Addictive Behaviors*, *36*(1-2), 125-128.

21. Carter, R. M., Meyer, J. R., & Huettel, S. A. (2010). Functional neuroimaging of intertemporal choice models: A review. *Journal of Neuroscience, Psychology, and Economics*, *3*(1), 27.
22. Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. *Journal of personality and social psychology*, *67*(2), 319.
23. Chabris, C. F., Laibson, D. I., & Schuldt, J. P. (2010). Intertemporal choice. In *Behavioural and Experimental Economics* (pp. 168-177). Palgrave Macmillan, London.
24. Chapman, G. B. (1996). Temporal discounting and utility for health and money. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *22*(3), 771.
25. Chapman, G. B., & Elstein, A. S. (1995). Valuing the future: Temporal discounting of health and money. *Medical decision making*, *15*(4), 373-386.
26. Charlton, S. R., & Fantino, E. (2008). Commodity specific rates of temporal discounting: does metabolic function underlie differences in rates of discounting?. *Behavioural processes*, *77*(3), 334-342.
27. Childwise. (2020). Monitor Report 2020. Retrieved March 3, 2022, from https://www.childwise.co.uk/monitor.html
28. Chiu, S. I. (2014). The relationship between life stress and smartphone addiction on Taiwanese university student: A mediation model of learning self-efficacy and social self-efficacy. *Computers in human behavior*, *34*, 49-57.
29. Coffey, S. F., Gudleski, G. D., Saladin, M. E., & Brady, K. T. (2003). Impulsivity and rapid discounting of delayed hypothetical rewards in cocaine-dependent individuals. *Experimental and clinical psychopharmacology*, *11*(1), 18.
30. Daniel, T. O., Stanton, C. M., & Epstein, L. H. (2013). The future is now: Comparing the effect of episodic future thinking on impulsivity in lean and obese individuals. *Appetite*, *71*, 120-125.
31. Data.ai. (2021). State of Mobile 2021. Retrieved March 2, 2022, from https://www.data.ai/en/go/state-of-mobile-2021/?sfdcid=7016F000002MS1c
32. David, M. E., Roberts, J. A., & Christenson, B. (2018). Too much of a good thing: Investigating the association between actual smartphone use and

individual well-being. *International Journal of Human–Computer Interaction*, *34*(3), 265-275.
33. DeHart, W. B., & Odum, A. L. (2015). The effects of the framing of time on delay discounting. *Journal of the experimental analysis of behavior*, *103*(1), 10-21.
34. Demurie, E., Roeyers, H., Baeyens, D., & Sonuga-Barke, E. (2013). Domain-general and domain-specific aspects of temporal discounting in children with ADHD and autism spectrum disorders (ASD): A proof of concept study. *Research in developmental disabilities*, *34*(6), 1870-1880.
35. DeSteno, D., Li, Y., Dickens, L., & Lerner, J. S. (2014). Gratitude: A tool for reducing economic impatience. *Psychological science*, *25*(6), 1262-1267.
36. Dixon, M. R., Jacobs, E. A., & Sanders, S. (2006). Contextual control of delay discounting by pathological gamblers. *Journal of applied behavior analysis*, *39*(4), 413-422.
37. Du, W., Green, L., & Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record*, *52*(4), 479-492.
38. Duckworth, A. L., & Kern, M. L. (2011). A meta-analysis of the convergent validity of self-control measures. *Journal of research in personality*, *45*(3), 259-268.
39. Duckworth, A. L., Taxer, J. L., Eskreis-Winkler, L., Galla, B. M., & Gross, J. J. (2019). Self-control and academic achievement. *Annual review of psychology*, *70*, 373-399.
40. Duncan, M. J., Vandelanotte, C., Caperchione, C., Hanley, C., & Mummery, W. K. (2012). Temporal trends in and relationships between screen time, physical activity, overweight and obesity. *BMC Public Health*, *12*(1), 1-9.
41. Eisenberg, D. T., MacKillop, J., Modi, M., Beauchemin, J., Dang, D., Lisman, S. A., ... & Wilson, D. S. (2007). Examining impulsivity as an endophenotype using a behavioral approach: a DRD2 TaqI A and DRD4 48-bp VNTR association study. *Behavioral and Brain Functions*, *3*(1), 1-14.
42. Ellis, D. A. (2019). Are smartphones really that bad? Improving the psychological measurement of technology-related behaviors. *Computers in Human Behavior*, *97*, 60-66.

43. Ellis, D. A., Davidson, B. I., Shaw, H., & Geyer, K. (2019). Do smartphone usage scales predict behavior?. *International Journal of Human-Computer Studies*, *130*, 86-92.
44. Epstein, L. H., Salvy, S. J., Carr, K. A., Dearing, K. K., & Bickel, W. K. (2010). Food reinforcement, delay discounting and obesity. *Physiology & behavior*, *100*(5), 438-445.
45. Estle, S. J., Green, L., Myerson, J., & Holt, D. D. (2007). Discounting of monetary and directly consumable rewards. *Psychological science*, *18*(1), 58-63.
46. Evenden, J. L. (1999). Varieties of impulsivity. *Psychopharmacology*, *146*(4), 348-361.
47. Everitt, B. J., & Robbins, T. W. (2005). Neural systems of reinforcement for drug addiction: from actions to habits to compulsion. *Nature neuroscience*, *8*(11), 1481-1489.
48. Fareri, D. S., & Delgado, M. R. (2014). Social Rewards and Social Networks in the Human Brain. The Neuroscientist, 20(4), 387–402. https://doi.org/10.1177/1073858414521869
49. Figner, B., Knoch, D., Johnson, E. J., Krosch, A. R., Lisanby, S. H., Fehr, E., & Weber, E. U. (2010). Lateral prefrontal cortex and self-control in intertemporal choice. *Nature neuroscience*, *13*(5), 538-539.
50. Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, *40*(2), 351-401.
51. Friedel, J. E., DeHart, W. B., Madden, G. J., & Odum, A. L. (2014). Impulsivity and cigarette smoking: Discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology*, *231*(23), 4517-4526.
52. Galanter, E. (1962). The direct measurement of utility and subjective probability. *The American journal of psychology*, *75*(2), 208-220.
53. Gately, D. (1980). Individual discount rates and the purchase and utilization of energy-using durables: Comment. *Bell Journal of Economics*, *11*(1), 373-374.

54. Gower, A. D., & Moreno, M. A. (2018). A novel approach to evaluating mobile smartphone screen time for iPhones: feasibility and preliminary findings. *JMIR mHealth and uHealth*, *6*(11), e11012.
55. Grace, R. C., & McLean, A. P. (2005). Integrated versus segregated accounting and the magnitude effect in temporal discounting. *Psychonomic Bulletin & Review*, *12*(4), 732-739.
56. Grant, J. E., Potenza, M. N., Weinstein, A., & Gorelick, D. A. (2010). Introduction to behavioral addictions. *The American journal of drug and alcohol abuse*, *36*(5), 233-241.
57. Green, L., Fristoe, N., & Myerson, J. (1994). Temporal discounting and preference reversals in choice between delayed outcomes. *Psychonomic Bulletin & Review*, *1*(3), 383-389.
58. Green, L., Myerson, J., & McFadden, E. (1997). Rate of temporal discounting decreases with amount of reward. *Memory & cognition*, *25*(5), 715-723.
59. 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.
60. Hale, L., & Guan, S. (2015). Screen time and sleep among school-aged children and adolescents: a systematic literature review. *Sleep medicine reviews*, *21*, 50-58.
61. Hammond, C. J., Mayes, L. C., & Potenza, M. N. (2014). Neurobiology of adolescent substance use and addictive behaviors: prevention and treatment implications. *Adolescent medicine: State of the art reviews*, *25*(1), 15.
62. Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 33-54.
63. Hawi, N. S., & Samaha, M. (2016). To excel or not to excel: Strong evidence on the adverse effect of smartphone addiction on academic performance. *Computers & Education*, *98*, 81-89.
64. Hawi, N. S., Samaha, M., & Griffiths, M. D. (2019). The digital addiction scale for children: Development and validation. *Cyberpsychology, Behavior, and Social Networking*, *22*(12), 771-778.

65. Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. http://www.afhayes.com/public/process2012.pdf
66. Herrmann, E. S., Hand, D. J., Johnson, M. W., Badger, G. J., & Heil, S. H. (2014). Examining delay discounting of condom-protected sex among opioid-dependent women and non-drug-using control women. *Drug and alcohol dependence*, *144*, 53-60.
67. Hofmann, W., Reinecke, L., & Meier, A. (2016). Of Sweet Temptations and Bitter Aftertaste: Self-Control as a Moderator of the Efects of Media Use on Well-Being. *The Routledge handbook of media use and well-being*, 229-240.
68. Holt, D. D., Glodowski, K., Smits-Seemann, R. R., & Tiry, A. M. (2016). The domain effect in delay discounting: The roles of fungibility and perishability. *Behavioural processes*, *131*, 47-52.
69. Hsee, C. K., Abelson, R. P., & Salovey, P. (1991). The relative weighting of position and velocity in satisfaction. *Psychological science*, *2*(4), 263-267.
70. Jimura, K., Myerson, J., Hilgard, J., Braver, T. S., & Green, L. (2009). Are people really more patient than other animals? Evidence from human discounting of real liquid rewards. *Psychonomic bulletin & review*, *16*(6), 1071-1075.
71. Johnson, M. W., & Bickel, W. K. (2002). Within-subject comparison of real and hypothetical money rewards in delay discounting. *Journal of the experimental analysis of behavior*, *77*(2), 129-146.
72. Johnson, M. W., & Bruner, N. R. (2012). The Sexual Discounting Task: HIV risk behavior and the discounting of delayed sexual rewards in cocaine dependence. *Drug and alcohol dependence*, *123*(1-3), 15-21.
73. Kable, J. W., & Glimcher, P. W. (2007). The neural correlates of subjective value during intertemporal choice. *Nature neuroscience*, *10*(12), 1625-1633.
74. Kable, J. W., & Glimcher, P. W. (2009). The neurobiology of decision: consensus and controversy. *Neuron*, *63*(6), 733-745.
75. Kalivas, P. W., & Volkow, N. D. (2005). The neural basis of addiction: a pathology of motivation and choice. *American Journal of Psychiatry*, *162*(8), 1403-1413.
76. Kelley, N. J., & Schmeichel, B. J. (2015). Thinking about death reduces delay discounting. *PloS One*, *10*(12), e0144228.

77. Killeen, P. R. (2009). An additive-utility model of delay discounting. *Psychological review*, *116*(3), 602.
78. Kirby, K. N. (1997). Bidding on the future: Evidence against normative discounting of delayed rewards. *Journal of Experimental Psychology: General*, *126*(1), 54.
79. Kirby, K. N. (2009). One-year temporal stability of delay-discount rates. *Psychonomic bulletin & review*, *16*(3), 457-462.
80. Kirby, K. N., & Maraković, N. N. (1996). Modeling myopic decisions: Evidence for hyperbolic delay-discounting within subjects and amounts. *Organizational Behavior and Human decision processes*, *64*(1), 22-30.
81. 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.
82. Kolb, B., & Gibb, R. (2011). Brain plasticity and behaviour in the developing brain. *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, *20*(4), 265.
83. Koopmans, T. C. (1960). Stationary ordinal utility and impatience. *Econometrica: Journal of the Econometric Society*, 287-309.
84. Kringelbach, M. L., & Rolls, E. T. (2004). The functional neuroanatomy of the human orbitofrontal cortex: evidence from neuroimaging and neuropsychology. *Progress in neurobiology*, *72*(5), 341-372.
85. Kuhn, T. S. (1970). *The Structure of Scientific Revolutions, 2nd enl. ed*. University of Chicago Press.
86. Kwan, D., Craver, C. F., Green, L., Myerson, J., Gao, F., Black, S. E., & Rosenbaum, R. S. (2015). Cueing the personal future to reduce discounting in intertemporal choice: Is episodic prospection necessary?. *Hippocampus*, *25*(4), 432-443.
87. Lagorio, C. H., & Madden, G. J. (2005). Delay discounting of real and hypothetical rewards III: Steady-state assessments, forced-choice trials, and all real rewards. *Behavioural processes*, *69*(2), 173-187.
88. Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, *112*(2), 443-478.

89. Lin, Y. H., Chang, L. R., Lee, Y. H., Tseng, H. W., Kuo, T. B., & Chen, S. H. (2014). Development and validation of the Smartphone Addiction Inventory (SPAI). *PloS one*, *9*(6), e98312.
90. Lin, Y. H., Chiang, C. L., Lin, P. H., Chang, L. R., Ko, C. H., Lee, Y. H., & Lin, S. H. (2016). Proposed diagnostic criteria for smartphone addiction. *PloS one*, *11*(11), e0163010.
91. 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), 1-10.
92. Loewenstein, G. F., & Prelec, D. (1993). Preferences for sequences of outcomes. *Psychological review*, *100*(1), 91.
93. Loewenstein, G., Read, D., & Baumeister, R. F. (Eds.). (2003). *Time and decision: Economic and psychological perspectives of intertemporal choice*. Russell Sage Foundation.
94. Loewenstein, G., & Thaler, R. H. (1989). Anomalies: intertemporal choice. *Journal of Economic perspectives*, *3*(4), 181-193.
95. Logothetis, N. K., Pauls, J., Augath, M., Trinath, T., & Oeltermann, A. (2001). Neurophysiological investigation of the basis of the fMRI signal. *nature*, *412*(6843), 150-157.
96. Luo, S., Ainslie, G., Giragosian, L., & Monterosso, J. R. (2009). Behavioral and neural evidence of incentive bias for immediate rewards relative to preference-matched delayed rewards. *Journal of Neuroscience*, *29*(47), 14820-14827.
97. Mackie, M. A., Van Dam, N. T., & Fan, J. (2013). Cognitive control and attentional functions. *Brain and cognition*, *82*(3), 301-312.
98. MacKillop, J., Amlung, M. T., Few, L. R., Ray, L. A., Sweet, L. H., & Munafò, M. R. (2011). Delayed reward discounting and addictive behavior: a meta-analysis. *Psychopharmacology*, *216*(3), 305-321.
99. 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.
100. Madden, G. J., & Bickel, W. K. (2010). *Impulsivity: The behavioral and neurological science of discounting*. American Psychological Association.

101. Madden, G. J., Petry, N. M., Badger, G. J., & Bickel, W. K. (1997). Impulsive and self-control choices in opioid-dependent patients and non-drug-using control patients: Drug and monetary rewards. *Experimental and clinical psychopharmacology*, *5*(3), 256.
102. Marco-Pallarés, J., Mohammadi, B., Samii, A., & Münte, T. F. (2010). Brain activations reflect individual discount rates in intertemporal choice. *Brain Research*, *1320*, 123-129.
103. Marzilli Ericson, K. M., White, J. M., Laibson, D., & Cohen, J. D. (2015). Money earlier or later? Simple heuristics explain intertemporal choices better than delay discounting does. *Psychological science*, *26*(6), 826-833.
104. Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. *Commons, ML.; Mazur, JE.; Nevin, JA*, 55-73.
105. McClure, S. M., & Bickel, W. K. (2014). A dual-systems perspective on addiction: contributions from neuroimaging and cognitive training. *Annals of the New York Academy of Sciences*, *1327*(1), 62-78.
106. McClure, S. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science*, *306*(5695), 503-507.
107. McKerchar, T. L., Green, L., Myerson, J., Pickford, T. S., Hill, J. C., & Stout, S. C. (2009). A comparison of four models of delay discounting in humans. *Behavioural processes*, *81*(2), 256-259.
108. Meshi, D., Tamir, D. I., & Heekeren, H. R. (2015). The emerging neuroscience of social media. *Trends in cognitive sciences*, *19*(12), 771-782.
109. Miller, E. K., Freedman, D. J., & Wallis, J. D. (2002). The prefrontal cortex: categories, concepts and cognition. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *357*(1424), 1123-1136.
110. Mischel, W., Shoda, Y., & Rodriguez, M. L. (1989). Delay of gratification in children. *Science*, *244*(4907), 933-938.
111. Mitchell, S. H. (1999). Measures of impulsivity in cigarette smokers and non-smokers. *Psychopharmacology*, *146*(4), 455-464.
112. Moore, M. J., & Viscusi, W. K. (1990). Models for estimating discount rates for long-term health risks using labor market data. *Journal of Risk and uncertainty*, *3*(4), 381-401.

113. Morgenstern, O., & Von Neumann, J. (1953). *Theory of games and economic behavior*. Princeton university press.
114. Morrison, K. L., Madden, G. J., Odum, A. L., Friedel, J. E., & Twohig, M. P. (2014). Altering impulsive decision making with an acceptance-based procedure. *Behavior therapy*, *45*(5), 630-639.
115. Myerson, J., Baumann, A. A., & Green, L. (2014). Discounting of delayed rewards:(A) theoretical interpretation of the Kirby questionnaire. *Behavioural processes*, *107*, 99-105.
116. Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the experimental analysis of behavior*, *64*(3), 263-276.
117. Nelson, C. A. (1999). Neural plasticity and human development. *Current directions in psychological science*, *8*(2), 42-45.
118. Nicolai, J., & Moshagen, M. (2017). Dissociating pathological buying from obsessive-compulsive symptoms using delay discounting. *Zeitschrift für Psychologie*.
119. Odum, A. L. (2011). Delay discounting: I'm ak, you're ak. *Journal of the experimental analysis of behavior*, *96*(3), 427-439.
120. Odum, A. L. (2011). Delay discounting: trait variable?. *Behavioural processes*, *87*(1), 1-9.
121. Odum, A. L., Becker, R. J., Haynes, J. M., Galizio, A., Frye, C. C., Downey, H., ... & Perez, D. M. (2020). Delay discounting of different outcomes: Review and theory. *Journal of the experimental analysis of behavior*, *113*(3), 657-679.
122. Odum, A. L., & Rainaud, C. P. (2003). Discounting of delayed hypothetical money, alcohol, and food. *Behavioural processes*, *64*(3), 305-313.
123. Ohmura, Y., Takahashi, T., Kitamura, N., & Wehr, P. (2006). Three-month stability of delay and probability discounting measures. *Experimental and clinical psychopharmacology*, *14*(3), 318.
124. Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction?. *Journal of behavioral addictions*, *7*(2), 252-259.
125. Patton, J. H., Stanford, M. S., & Barratt, E. S. (1995). Factor structure of the Barratt impulsiveness scale. *Journal of clinical psychology*, *51*(6), 768-774.
126. Pearl, J. (2009). *Causality*. Cambridge university press.

127. Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural India. *Journal of development Economics*, *50*(2), 257-296.
128. Peters, J., & Büchel, C. (2009). Overlapping and distinct neural systems code for subjective value during intertemporal and risky decision making. *Journal of Neuroscience*, *29*(50), 15727-15734.
129. Peters, J., & Büchel, C. (2010). Episodic future thinking reduces reward delay discounting through an enhancement of prefrontal-mediotemporal interactions. *Neuron*, *66*(1), 138-148.
130. Peters, J., & Büchel, C. (2011). The neural mechanisms of inter-temporal decision-making: understanding variability. *Trends in cognitive sciences*, *15*(5), 227-239.
131. Petry, N. M. (2001). Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. *Psychopharmacology*, *154*(3), 243-250.
132. Petry, N. M. (2001). Substance abuse, pathological gambling, and impulsiveness. *Drug and alcohol dependence*, *63*(1), 29-38.
133. Phelps, E. S., & Pollak, R. A. (1968). On second-best national saving and game-equilibrium growth. *The Review of Economic Studies*, *35*(2), 185-199.
134. Pochon, J. B., Riis, J., Sanfey, A. G., Nystrom, L. E., & Cohen, J. D. (2008). Functional imaging of decision conflict. *Journal of Neuroscience*, *28*(13), 3468-3473.
135. Rachlin, H., Raineri, A., & Cross, D. (1991). Subjective probability and delay. *Journal of the experimental analysis of behavior*, *55*(2), 233-244.
136. Redelmeier, D. A., & Heller, D. N. (1993). Time preference in medical decision making and cost-effectiveness analysis. *Medical Decision Making*, *13*(3), 212-217.
137. Reynolds, B. (2006). A review of delay-discounting research with humans: relations to drug use and gambling. *Behavioural pharmacology*, *17*(8), 651-667.
138. Robb, M. B. (2019). (rep.). *The New Normal: Parents, Teens, Screens, and Sleep* (pp. 9–9). San Francisco, CA: Common Sense Media.

139. Roberts, B. W., Wood, D., & Smith, J. L. (2005). Evaluating five factor theory and social investment perspectives on personality trait development. *Journal of Research in Personality*, *39*(1), 166-184.
140. Robles, E., & Vargas, P. A. (2008). Parameters of delay discounting assessment: Number of trials, effort, and sequential effects. *Behavioural Processes*, *78*(2), 285-290.
141. Ruderman, H., Levine, M. D., & McMahon, J. E. (1987). The behavior of the market for energy efficiency in residential appliances including heating and cooling equipment. *The Energy Journal*, *8*(1).
142. Rung, J. M., & Madden, G. J. (2018). Experimental reductions of delay discounting and impulsive choice: A systematic review and meta-analysis. *Journal of Experimental Psychology: General*, *147*(9), 1349.
143. Samuelson, P. A. (1937). A note on measurement of utility. *The review of economic studies*, *4*(2), 155-161.
144. Sasse, L. K., Peters, J., Büchel, C., & Brassen, S. (2015). Effects of prospective thinking on intertemporal choice: The role of familiarity. *Human brain mapping*, *36*(10), 4210-4221.
145. Schmidt, S. C., Anedda, B., Burchartz, A., Eichsteller, A., Kolb, S., Nigg, C., ... & Woll, A. (2020). Physical activity and screen time of children and adolescents before and during the COVID-19 lockdown in Germany: a natural experiment. *Scientific Reports*, *10*(1), 1-12.
146. Schulz van Endert, T. (2021). Addictive use of digital devices in young children: Associations with delay discounting, self-control and academic performance. *PloS one*, *16*(6), e0253058.
147. Schulz van Endert, T., & Mohr, P. N. (2020). Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting. *PloS one*, *15*(11), e0241383.
148. Schulz van Endert, T., & Mohr, P. N. (2022). Delay Discounting of Monetary and Social Media Rewards: Magnitude and Trait Effects. *Frontiers in Psychology*, *13*, 822505-822505.
149. Sellitto, M., Ciaramelli, E., & di Pellegrino, G. (2010). Myopic discounting of future rewards after medial orbitofrontal damage in humans. *Journal of Neuroscience*, *30*(49), 16429-16436.

150. Shelley, M. K. (1993). Outcome signs, question frames and discount rates. *Management Science*, *39*(7), 806-815.
151. 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.
152. 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.
153. Siegler, R. S. (1994). Cognitive variability: A key to understanding cognitive development. *Current directions in psychological science*, *3*(1), 1-5.
154. Simpson, C. A., & Vuchinich, R. E. (2000). Reliability of a measure of temporal discounting. *The Psychological Record*, *50*(1), 3-16.
155. Skinner, B. F. (1965). *Science and human behavior* (No. 92904). Simon and Schuster.
156. Smith, C. L., & Hantula, D. A. (2008). Methodological considerations in the study of delay discounting in intertemporal choice: A comparison of tasks and modes. *Behavior research methods*, *40*(4), 940-953.
157. Solitaired. (2021). Smartphone usage and screen time statistics 2021. Retrieved March 31, 2022, from https://solitaired.com/screen-time-statistics-2021
158. Spear, L. P. (2000). The adolescent brain and age-related behavioral manifestations. *Neuroscience & biobehavioral reviews*, *24*(4), 417-463.
159. Statista. (2021). Time spent with nonvoice activities on mobile phones every day in the United States from 2019 to 2023. Retrieved March 31, 2022, from https://www.statista.com/statistics/1045353/mobile-device-daily-usage-time-in-the-us/
160. Statista. (2022). Number of smartphone subscriptions worldwide from 2016 to 2027. Retrieved March 31, 2022, from https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/
161. Steinbeis, N., Haushofer, J., Fehr, E., & Singer, T. (2016). Development of behavioral control and associated vmPFC–DLPFC connectivity explains

children's increased resistance to temptation in intertemporal choice. *Cerebral Cortex*, *26*(1), 32-42.

162. Strathman, A., Gleicher, F., Boninger, D. S., & Edwards, C. S. (1994). The consideration of future consequences: weighing immediate and distant outcomes of behavior. *Journal of personality and social psychology*, *66*(4), 742.
163. Straus, M. A. (1962). Deferred gratification, social class, and the achievement syndrome. *American Sociological Review*, 326-335.
164. Strotz, R. H. (1955). Myopia and inconsistency in dynamic utility maximization. *The review of economic studies*, *23*(3), 165-180.
165. Tang, Y. Y., Posner, M. I., Rothbart, M. K., & Volkow, N. D. (2015). Circuitry of self-control and its role in reducing addiction. *Trends in cognitive sciences*, *19*(8), 439-444.
166. 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*, 363.
167. 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
168. Taubitz, L. E., Pedersen, W. S., & Larson, C. L. (2015). BAS Reward Responsiveness: A unique predictor of positive psychological functioning. *Personality and Individual Differences*, *80*, 107-112.
169. Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, *8*(3), 201-207.
170. Thomée, S., Härenstam, A., & Hagberg, M. (2011). Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults-a prospective cohort study. *BMC public health*, *11*(1), 1-11.
171. Tian, M., Tao, R., Zheng, Y., Zhang, H., Yang, G., Li, Q., & Liu, X. (2018). Internet gaming disorder in adolescents is linked to delay discounting but not probability discounting. *Computers in human behavior*, *80*, 59-66.
172. Vahedi, Z., & Saiphoo, A. (2018). The association between smartphone use, stress, and anxiety: A meta-analytic review. *Stress and Health*, *34*(3), 347-358.

173. Van der Wal, A. J., Schade, H. M., Krabbendam, L., & Van Vugt, M. (2013). Do natural landscapes reduce future discounting in humans?. *Proceedings of the Royal Society B: Biological Sciences*, *280*(1773), 20132295.
174. Viscusi, W. K., & Moore, M. J. (1989). Rates of time preference and valuations of the duration of life. *Journal of public economics*, *38*(3), 297-317.
175. Vom Orde, H., & Durner, A. (2021). International Data Youth and Media 2021. Retrieved March 02, 2022, from https://www.br-online.de/jugend/izi/english/International%20Data%20on%20Youth%20and%20Media.pdf
176. Vuchinich, R. E., & Simpson, C. A. (1998). Hyperbolic temporal discounting in social drinkers and problem drinkers. *Experimental and clinical psychopharmacology*, *6*(3), 292.
177. Weidberg, S., Landes, R. D., García-Rodríguez, O., Yoon, J. H., & Secades-Villa, R. (2015). Interaction effect of contingency management and sex on delay-discounting changes among treatment-seeking smokers. *Experimental and Clinical Psychopharmacology*, *23*(5), 361.
178. Weller, R. E., Cook III, E. W., Avsar, K. B., & Cox, J. E. (2008). Obese women show greater delay discounting than healthy-weight women. *Appetite*, *51*(3), 563-569.
179. Wheelwright, T. (2022, January 24). *2022 cell phone usage statistics: How obsessed are we?* Reviews.org. Retrieved February 14, 2022, from https://www.reviews.org/mobile/cell-phone-addiction/
180. Wilhelm, C. J., & Mitchell, S. (2009). Strain differences in delay discounting using inbred rats. *Genes, Brain and Behavior*, *8*(4), 426-434.
181. Wilkinson, N., & Klaes, M. (2017). *An introduction to behavioral economics*. Macmillan International Higher Education.
182. 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.
183. 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. *Social cognitive and affective neuroscience*, *14*(4), 367-379.

184. 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.
185. Yanbaeva, D. G., Dentener, M. A., Creutzberg, E. C., Wesseling, G., & Wouters, E. F. (2007). Systemic effects of smoking. *Chest*, *131*(5), 1557-1566.
186. Yeun, Y. R., & Han, S. J. (2016). Effects of psychosocial interventions for school-aged children's internet addiction, self-control and self-esteem: meta-analysis. *Healthcare Informatics Research*, *22*(3), 217-230.
187. Yi, R., Johnson, M. W., Giordano, L. A., Landes, R. D., Badger, G. J., & Bickel, W. K. (2008). The effects of reduced cigarette smoking on discounting future rewards: An initial evaluation. *The Psychological Record*, *58*(2), 163-174.
188. Zizzo, D. J. (2010). Experimenter demand effects in economic experiments. *Experimental Economics*, *13*(1), 75-98.

7. Appendix

7.1 Deutsche Zusammenfassung

Die Wahl zwischen Mahlzeiten bei McDonald's und einem fitten Körper, zwischen dem Genuss von Zigaretten und einer gesunden Lunge oder zwischen dem Scrollen auf sozialen Medien und der Fertigstellung einer Dissertation - diese allgegenwärtigen Entscheidungen erfordern das Abwägen von Kosten und Nutzen, welche zu verschiedenen Zeitpunkten auftreten. Ökonomen begannen bereits im 18. Jahrhundert diese Abwägungen, welche als intertemporale Entscheidungen bezeichnet werden, zu untersuchen. Sie fokussierten sich dabei jedoch auf deren Auswirkung auf den wirtschaftlichen Wohlstand statt auf Fragen der Ernährung, Gesundheit oder akademischen Leistungen. Trotz früher, differenzierter Überlegungen wurde in der ersten Hälfte des 20. Jahrhunderts eine simple Theorie der intertemporalen Entscheidungen, die sogenannte Discounted Utility Theorie, vorgestellt und breit angenommen. Ihren Kern bildet ein Modell, welches postuliert, dass Menschen jene Entscheidungsoption wählen, welche die Summe der damit verbundenen diskontierten Nutzenströme maximiert. Die expliziten und impliziten Annahmen des Discounted Utility Modells, welche nicht auf Basis von empirischer Evidenz entstand, wurden erst in der zweiten Hälfte des 20. Jahrhunderts von Psychologen anhand von Feldstudien und Experimenten kritisch geprüft. Zahlreiche Verhaltensanomalien wurden hierbei entdeckt, was zur Entwicklung von alternativen Modellen (z.B. hyperbolische Diskontierung) führte. Diese können eine deutlich höhere deskriptive Validität vorweisen. Seitdem floriert die Forschung an intertemporalen Entscheidungen und hat zahlreiche Erklärungen für verschiedenste Verhaltensphänomene hervorgebracht. Menschen treffen beispielsweise öfter als gewünscht eine sogenannte impulsive Wahl, d.h. eine kleinere, frühere Belohnung (z.B. ein Big Mac) wird einer größeren, verzögerten Belohnung (z.B. einem flachen Bauch) bevorzugt. Verhaltensökonomen führen dies auf einen zentralen Prozess zurück, der dieser Entscheidung unterliegt: Delay Discounting, d.h. die Tendenz Belohnungen in der Zukunft basierend auf ihrer Verzögerung zu diskontieren. Delay Discounting, oft vereinfachend als Impulsivität bezeichnet, hat sowohl Eigenschaften eines Merkmals als auch eines Zustands. Individuen haben eine stabile, zum Teil genetisch bestimmte Grundtendenz Belohnungen in der Zukunft zu diskontieren, welche sich aber auch geringfügig an den Entscheidungskontext anpassen kann. Zudem haben Neurowissenschaftler vor Kurzem damit begonnen, die neuronalen Mechanismen, welche Delay Discounting zugrunde liegen, zu untersuchen. Derzeit identifizieren sie die Bewertung von Belohnungen, die kognitive Kontrolle und die Prospektion als relevante Subprozesse im menschlichen Gehirn. Ein weiteres Forschungsergebnis mit hoher klinischer Relevanz ist die Assoziation von Delay Discounting mit zahlreichen problematischen Verhaltensweisen, wie z.B. dem Drogenkonsum, riskanten sexuellen Entscheidungen oder auch Verhaltenssüchten.

Parallel haben sich digitale Geräte wie Smartphones, Tablets und Laptops/PCs in der globalen Gesellschaft verbreitet. Dabei fällt auf, dass das Nutzungsverhalten von Erwachsenen und sogar Kindern vermehrt als exzessiv oder gar von einigen Wissenschaftlern als süchtig beschrieben wird. Dies wirft die Frage auf, ob nicht auch ein Zusammenhang zwischen der Nutzung von digitalen Geräten und Delay Discounting besteht; inwieweit kann der Gebrauch von Smartphones, Tablets und Laptops/PCs als impulsive Wahl betrachtet werden? Die Forschung dieser Dissertation hat drei empirische Untersuchungen zur jungen Literatur beigetragen. In der ersten Studie versuchten wir initiale Ergebnisse in Bezug auf die Assoziation von Smartphonenutzung und Impulsivität mithilfe von verlässlichen und differenzierten Methoden zu replizieren. In Anlehnung an aktuellen Erkenntnissen bezüglich der oben genannten neuronalen Mechanismen, die Delay Discounting unterliegen, analysierten wir ebenso die Rolle der Belohnungssensitivität, der Selbstkontrolle und der Berücksichtigung von Konsequenzen in der Zukunft. Wir fanden bei 101 teilnehmenden Studenten heraus, dass die objektiv gemessene Nutzungsdauer von Smartphones mit Delay Discounting zusammenhing. Diese statistische Beziehung wurde durch die Bildschirmzeit von sozialen Medien und Spiele-Apps getrieben. Außerdem wurde diese Assoziation von keiner der erhobenen psychologischen Variablen mediiert. Die zweite Studie untersuchte den Zusammenhang zwischen Delay Discounting und der suchtartigen Nutzung von digitalen Geräten durch 72 teilnehmende Kinder im Grundschulalter, d.h. deren Gebrauch verbunden mit negativen sozialen, physiologischen, psychologischen und schulischen Auswirkungen. In diesem Alter werden wesentliche Grundlagen für den späteren Lebenserfolg geschaffen. Assoziationen mit der Fähigkeit zur Selbstkontrolle und der akademischen Leistung der Kinder wurden ebenso analysiert. Die Ergebnisse zeigten, dass Schülerinnen und Schüler mit höherer Präferenz für kleinere, sofortige Belohnungen im Durchschnitt ein größeres Ausmaß von suchtartiger Nutzung digitaler Geräte aufwiesen. Dieser Zusammenhang wurde jedoch von der Fähigkeit der Kinder, ihre Gedanken, Emotionen und Handlungen zu kontrollieren, konfundiert. Zusätzlich waren Selbstkontrolle und Bildschirmzeit Prädiktoren des aktuellen Notendurchschnitts der Kinder. Die Untersuchung von Delay Discounting im Kontext von Belohnungen auf sozialen Medien, als wesentlicher Aspekt der Nutzung von digitalen Geräten, war das Ziel der dritten Studie. Wir konnten hier einerseits den Magnitudeneffekt von Delay Discounting (d.h. größere monetäre und nicht-monetäre Belohnungen werden weniger stark diskontiert als kleinere) auch bei Instagram-Followern und -Likes nachweisen. Andererseits korrelierten die Ausmaße der Diskontierung von Geld, Followern und Likes, was zusätzliche Evidenz für Delay Discounting als Merkmal lieferte. In der Gesamtbetrachtung zeigte die Forschung dieser Dissertation einen signifikanten obgleich schwachen Zusammenhang zwischen der Nutzung von digitalen Geräten und der impulsiven Wahl. Die Richtung der Kausalität bleibt weiterhin offen und deren Feststellung bedarf weiterer umfangreicher (Langzeit-)Studien mit möglichst repräsentativen Stichproben. Die Fähigkeit zur Selbstkontrolle scheint jedoch insbesondere bei Kindern negative Auswirkungen der Smartphone-, Tablet- und Laptop-/PC-Nutzung abzumildern. Darüber hinaus zeigten die Studien die Wichtigkeit eines differenzierten Blicks auf die Nutzung von digitalen Geräten auf, wobei in zukünftigen Studien besondere Aufmerksamkeit auf ihre Belohnungsmechanismen gerichtet werden sollte.

7.2 Erklärung gem. § 10 Abs. 3

Berlin, den 1.4.2022

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe:

Quellen siehe Literaturverzeichnis

Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst. Es wurden keine anderen als die angegebenen Quellen und Hilfsmittel verwendet. Geistiges Eigentum anderer Autoren wurde als entsprechend gekennzeichnet. Ebenso versichere ich, dass ich an keiner anderen Stelle ein Prüfungsverfahren beantragt bzw. die Dissertation in dieser oder anderer Form an keiner anderen Fakultät als Dissertation vorgelegt habe.

Tim Schulz van Endert

7.3 Dissertation studies

RESEARCH ARTICLE

Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting

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Abstract

The omnipresence of smartphones among adolescents and adults gives rise to the questions about excessive use and personality factors which are associated with heavier engagement with these devices. Previous studies have found behavioral similarities between smartphone use and maladaptive behaviors (e.g. drinking, gambling, drug abuse) in the context of intertemporal choice but mostly relied on participants' self-reports regarding engagement with their phone. In this study, we collected actual usage data by smartphone application from 101 participants and assessed their tendency to discount future rewards, their reward responsiveness, self-control and consideration of future consequences. We found that smartphone screen time was correlated with choosing smaller immediate over larger delayed rewards and that usage of social media and gaming apps predicted delay discounting. Additionally, smartphone use was negatively correlated with self-control but not correlated with consideration of future consequences. Neither psychological variable could mediate the relationship between smartphone usage and delay discounting. Our findings provide further evidence that smartphone use and impulsive decision-making go hand in hand and that engagement with these devices needs to be critically examined by researchers to guide prudent behavior.

Introduction

For most people in the developed world the smartphone has become a constant companion. Recent surveys estimate that 76% of adults in advanced economies own a smartphone [1] while the penetration among adolescents has reached more than 80% [2]. Depending on the geography of the sample and the research methodology, the average duration for which smartphone owners are actively engaged with their devices ranges from 4.7 hours [3] to 8.8 hours per day [4]. Furthermore, more than 33% of smartphone users report that they access their smartphones within the first five minutes of waking up in the morning and more than 40% check their phone during the night [5].

decision to publish, or preparation of the manuscript.

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These statistics have naturally given rise to the question about excessive use of smartphones and its implications. Frequent notifications, immediate access to information and social feedback may make it difficult to refrain from engaging with the device, even if it is inappropriate or even dangerous (e.g. while driving) to do so [6]. While the concept of smartphone addiction is not yet included in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), several authors have found significant overlap between excessive smartphone use and substance-related disorders defined in the DSM-5 [7, 8]. Approaching the issue from a different angle, cognitive scientists have started to look at individual differences in functions such as attention [9], memory [10] and decision-making [11] and their relationships with smartphone use. Due to the relative novelty of smartphones, this research field is still in its infancy but dynamically growing [6]. One strand of the literature, which investigates the association between smartphone usage and impulsive choice, i.e. an individual's preference for smaller, immediate rewards over larger, delayed rewards has been a particularly fruitful avenue for research.

Human and non-human animals typically discount rewards as a function of the delay of their delivery, implying that a reward received today is worth more than the same reward received at a later point in time [12]. This tendency is referred to as delay discounting and is revealed in intertemporal choice problems, where participants are faced with the tradeoff between the delay and the amount of a reward (e.g. choosing 50€ today or 55€ in one week). Delay discounting has been studied thoroughly in the past decades, resulting in the emergence of two main models which seek to capture intertemporal choice behavior: exponential and hyperbolic discounting, the latter providing a better fit to the majority of empirical data [12]. The corresponding equation $V = A / (1+kD)$ (V is the present value of the future reward, A is the reward amount and D is the delay to the reward) contains one free parameter k, which represents an individual's discount rate. The larger this discounting parameter, the more the individual devalues remote rewards and is therefore relatively more impulsive than a person with a lower discount rate. Individuals' discount rates have been shown to be relatively stable over time, which is why delay discounting is widely considered to be similar to a personality trait [13, 14]. Furthermore, delay discounting has been associated with a host of maladaptive behaviors, such as drug abuse [15] problematic drinking [16] and gambling [17]. Studies have repeatedly shown that addicts discount future rewards more extremely than control participants, making the degree of delay discounting a reliable indicator for addictions of different nature [14].

While the concept of smartphone addiction is still under debate, researchers agree that impulsive decision-making as revealed in delay discounting paradigms is a relevant factor in the context of smartphone use [18, 19]. On the one hand, there is substantial evidence that social media, messaging and gaming—the most popular activities on smartphones [20–24]–are characterized by activation of primarily reward-related brain regions [25–29], highlighting the central role that gratification plays in engagement with the smartphone. On the other hand, excessive smartphone use has also been shown to have a negative impact on important parameters, such as sleep quality [30], stress levels [31], academic success [32] or overall well-being [33]. Thus, high smartphone users implicitly face a trade-off between gratification in the present and adverse consequences in the future.

First studies have indicated a positive association between smartphone usage and the discounting of future rewards. Wilmer and Chein [18] found that heavier engagement with the phone was positively correlated with an individual's discounting rate and greater impulsivity, the latter being assessed via a questionnaire and a behavioral measure. Similarly, Tang et al. [19] found that high and medium smartphone users in their sample more often chose a smaller immediate reward than low users and showed a bias in evaluating the time and monetary value dimension within an intertemporal choice task. In another study focusing on one aspect of smartphone usage, Delaney et al. [34] found that Facebook addicts discounted future rewards more heavily than matched controls. In a comprehensive field experiment Hadar et al. [35] compared a group of heavy smartphone users, as determined by questionnaires and verified by usage data recorded over a seven-day period, to a group lacking any experience with smartphones on a range of behavioral measures. Among other cognitive differences, they found that the heavy users behaved more impulsively within a delay discounting paradigm than the non-users. Additionally, to allow for causal claims regarding behavioral and neural changes associated with three-month smartphone exposure the authors also compared non-smartphone users to participants who received smartphones for the first time. The authors, however, could not observe an effect of smartphone usage on delay discounting.

These studies have provided initial valuable insights about the relationship between smartphone usage and delay discounting. However, they also exhibit two limitations, which may on the one hand challenge the reliability of the results and on the other hand restrict the conclusions which can be drawn from their findings. The first limitation concerns the measurement method of smartphone usage; previous studies have mostly relied on participants' self-reports regarding the patterns of smartphone engagement. Typically, questionnaires such as the Smartphone Addiction Scale [36] or the Smartphone Addiction Inventory [7] are used to group participants into heavy and low users. While these scales have been proven to reliably measure smartphone addiction, they are based on subjective statements (e.g. "My life would be empty without my smartphone") rather than on objective criteria such as screen time or checking behavior and therefore may not be the most suitable instruments to measure engagement with the smartphone. In a few instances, participants are directly asked to estimate how much time they spend with smartphone apps or how often they check their phones. Recent studies have shown that these kinds of self-reports are often unreliable due to participants' limited capacity in correctly estimating engagement with their phones. Kobayashi and Boase [37] found that Japanese phone users overestimated the number of calls made and text messages sent. Similarly, Boase and Ling [38] concluded that self-reports about calls and text messages correlated only moderately with actual log data of their large Norwegian sample. Andrews et al. [39] came up with similar results, finding that the estimated number of times an individual used her phone on a typical day did not correlate with actual usage and that neither estimated nor actual usage was related to scores on the Mobile Phone Problem Use Scale [40]. As an exception, Hadar et al. [35] also recorded actual usage data by means of an application, which was installed on participants' smartphones at the beginning of their experiment. While this enabled the authors to verify their initial questionnaire-based grouping of participants into high and low users, participants became aware that their usage was being observed. This awareness may on the one hand affect participants' natural smartphone-related behavior and on the other hand change the way participants behave in tasks aimed at measuring the effects of smartphone usage [6].

The second limitation is constituted by the scope of the assessment of smartphone usage. Either this variable is assessed broadly (i.e. overall engagement with the device, without regard of the specific apps/functionalities used) or narrowly by focusing on one out of the many aspects of smartphone engagement, such as social media. Both approaches do not allow for the identification of drivers of the relationship between smartphone engagement and delay discounting. However, a novel method leveraging the native Apple iOS feature "battery usage" has made it possible to overcome the above-mentioned measurement issues [23]. For this, researchers collect data from participants' iPhones which show the exact duration of all applications used recently. In addition to providing a comprehensive picture of individuals' usage patterns, this method is also non-intrusive as participants are not aware that their usage data are collected, as opposed to e.g. installing an app which records usage data and thereby potentially influencing naturalistic behavior.

This method has already been employed successfully when relating smartphone usage to other variables, such as well-being [22].

Furthermore, a promising neuroscientific model has emerged recently, which seeks to explain the mechanisms underlying intertemporal choice. According to this model, the variability in people's tendency to discount delayed rewards may be explained by individual differences in reward valuation, cognitive control and the ability to imagine future outcomes of decisions (prospection) [14]. Investigating these three personal dispositions and the nature of their relationships with smartphone usage as well as delay discounting may further our understanding of the variables associated with excessive use.

Thus, to replicate and extend previous findings on the relationship between smartphone usage and delay discounting, this study investigates the following two hypotheses:

Hypothesis 1: Actual smartphone usage is positively correlated with the tendency to discount future rewards (delay discounting).

Hypothesis 2: The relationship between smartphone usage and delay discounting is mediated by reward valuation, cognitive control and prospection.

We collected, in addition to self-reports, actual usage data by application from a sample, which is characterized by widespread smartphone ownership. In parallel, we elicited delay discounting with a widely used intertemporal choice paradigm along with personal dispositions. Our study contributes to the literature by showing a relationship between delay discounting and smartphone usage based on actual usage data, by uncovering two app categories which predict delay discounting and by demonstrating a link between self-control and smartphone usage.

Methods

Participants

116 participants (53% female, mean age 22 years) were recruited from the volunteer database of the Berlin Social Science Center (WZB) using the software ORSEE [41]. Six participants declined to provide their phone usage data upon arrival at the experiment, but took part in all other parts of the study. For five participants the usage data was not available due to an outdated or malfunctional operating system. Usage data of another four participants were not usable, since they brought a spare or a borrowed phone to the experiment. Net of these data points, data from 101 participants (52% female) were included in the analysis.

Measures

Net screen time. To assess how long and for which activities participants used their smartphone, data provided by the iOS feature "Battery usage" were collected. For every application this feature shows how long it was actively used on screen and how long it was running in the background without the user engaging with it, but still consuming battery life. These durations were mostly available for the timeframe of the last ten days, on older iOS versions of the last seven days. Since this is a native iOS feature, users have no influence on the logging of their usage, ensuring objective and consistent data. The feature also shows grand total screen time, which was used as a reliability check when app usage was coded and summed up for analysis. In order to get an estimate of a subject's average daily phone use, the total active screen time was divided by the timeframe indicated on the phone. To control for unusually long or short screen time at the time of data collection, participants had to report if their smartphone use was either unusually low, high or average within the last seven to ten days. If a subject indicated unusual usage and their self-reported usage differed from actual usage by more than 100%, participants were excluded from the analysis, which was not the case in our sample.

During data collection it became evident that some applications were used by almost all participants (e.g. WhatsApp, Facebook), while a vast amount of apps was installed only on few phones. Therefore, to allow for meaningful analyses screen time of apps that were used by less than a quarter of participants or had identical purposes (e.g. Safari and Chrome, Apple Mail and Yahoo Mail) was cumulated. This resulted in 11 distinct categories (see S1 Table for categorization). Additionally, in calculating net screen time we deducted screen time of applications related to music (e.g. Apple Music), TV (e.g. Netflix) and functionalities such as calling and GPS since these apps were characterized by passive usage, i.e. app running mostly in the background and/or requiring negligible interaction with the user. We assumed that inclusion of these usage patterns would distort the data; some participants had similar total screen time but in some cases this consisted mostly of social media use while in other instances the majority of active usage was due to GPS navigation.

Self-reported smartphone usage. Furthermore, to be able to compare these objective data to participants' self-reports, four questions assessed phone-related behavior of the participants: 1) "how much time on average do you spend on app . . .", 2) "how often do you usually post content or send messages on app . . . ", 3) "in which intervals do you normally check your phone for notifications" and 4) "after receiving a notification, how quickly do you click on it".

Delay discounting. The tendency to prefer smaller immediate rewards over larger delayed rewards was assessed using a German translation of the 27-item Monetary Choice Questionnaire [15]. In this questionnaire participants have to repeatedly choose between a smaller reward available immediately (e.g. €15 today) or a larger reward available in the future (e.g. €35 in 13 days). All rewards are hypothetical and consist of small (e.g. €15), medium (e.g. €41) and large amounts of money (e.g. €80). The proportion of choices of the larger delayed reward (LDR) serves as a measure of impulsivity, i.e. the lower the proportion, the more impulsive the individual. The scale is widely used in the literature and provides similar results to more extended instruments [42]. Also, it is a robust finding that using hypothetical rather than real or potentially real rewards yields virtually the same results [43]. Furthermore, the proportion of LDR measure is a simple yet reliable and valid measure, which, unlike estimating the discounting rate using the method by Kirby et al. [15], does not assume hyperbolic discounting [44]. The responses to the MCQ were scored using automated scoring [45]. This tool also provides consistency scores to enable identification of a lack of attending to the questionnaire. None of our participants had consistency scores below 75%, indicating good quality of responses [46].

Reward valuation. In this study the neural process of reward valuation was operationalized as an individual's responsiveness to rewards, which was elicited using the behavioral inhibition system/behavioral approach system (BIS/BAS) scales [47]. The scales measure an individual's degree of behavioral inhibition and behavioral activation, the latter being subdivided into Drive, Reward Responsiveness and Fun Seeking. Rather than just using the Reward Responsiveness subscale, the full 24-item questionnaire with its mixed order of questions and filler items was administered to enable the best possible accuracy of results. The German version of the scales by Strobel et al. [48] were used for this study. While the full BAS scale showed acceptable internal consistency ($\alpha = 0.73$), Cronbach's alpha for the Reward Responsiveness subscale was low ($\alpha = 0.56$) and therefore excluded from further analyses.

Cognitive control. We employed both a self-report as well as a behavioral measure of self-control, which has been shown to be closely linked to cognitive control processes [49]. For the self-report measure, we used the German adaptation by Bertrams and Dickhäuser [50] of Tangney et al.'s [51] brief self-control scale. Ample research has shown that the 13-item brief self-control scale yields reliable and valid results in assessing dispositional self-control capacity and performs similarly well compared to the less economical full 36-item version [51]. The internal consistency for this scale was acceptable ($\alpha = 0.74$).

As a behavioral measure, we employed the Go/No-Go task as a test of response inhibition. In this task, participants have to respond as quickly as possible to rapidly-presented target ("Go") cues shown on a computer screen. However, they have to withhold this response to non-target ("No-Go") cues, which appear less frequently. Commission errors (i.e. responses to non-targets) are a measure of reduced impulse control. We implemented an adaptation of the task by Mostofsky et al. [52] in which green circles are used as target cues, to which participants have to respond by pressing the space bar, and red Xs as non-target cues; targets and non-targets were presented in a pseudorandom order. There were 127 Go-trials and 23 No-Go-trials per run; every 30 trials participants had a 10-second rest period to enable recovery of hemodynamic response. Participants completed two runs overall with a short self-determined rest period in between. Cues were shown for 200ms centered on a black screen. The intertrial-interval was 1,300ms during which a white fixation cross appeared in the center of the screen. The entire task took approx. 10 minutes to complete. In a pilot session, we determined that some participants did not exert full effort, e.g. by constantly pressing the space bar or by not responding at all. Therefore, to incentivize the task performance (measured by the error rate) we included in the instructions that the top 50% of participants would receive €2 for the task in addition to the base compensation, while the bottom 50% would receive no additional money. This resulted in having no shirkers in the main sessions.

Prospection. There are currently no established instruments that are suitable to measure an individual's ability to imagine future experiences in healthy participants. Therefore, we used as a proxy the inclination to consider distant versus immediate consequences of potential behavior as measured by the consideration of future consequences (CFC) scale [53]. The CFC construct is conceptually similar to delay discounting and is likewise related to problematic behaviors [54], but may better reveal individual differences in the ability to project the self into the future as seen in day-to-day behavior [55]. The German translation of the 12-item questionnaire by Bruderer Enzler [56] was used. The internal consistency for this scale was good ($\alpha = 0.80$).

Procedure

In their invitations, participants were told that they needed to be iPhone users and bring their phone to the experiment. However, they were not informed about the experimental objective and methods to avoid participants from adapting their naturalistic behavior. The experiment was conducted in seven sessions. At the beginning of each session, participants were instructed about the tasks and in particular, the phone usage data collection and signed informed consent documents. They were, however, not allowed to access their phones until the end of the experiment. Participants then completed the Go/No-Go task followed by a simple five-minute long decision task, which was not relevant to this study. The experiment continued with the Monetary Choice Questionnaire, the BIS/BAS scale, the brief self-control scale and the consideration of future consequences scale. Lastly, phone use data was collected by taking photographs of the battery use screens on the participants' phones. These data were entered into a spreadsheet after completion of each session. The order of tasks in our experiment was fixed throughout all sessions. On average, one session lasted about 50 minutes and participants received €16 in compensation. This study was approved by the German Association for Experimental Economic Research e.V. (approval no. xQ1XKNtp).

Results

Delay discounting and smartphone usage

The primary goal of this study was to determine if there was a positive relationship between actual smartphone usage and delay discounting. Indeed, we found a significant negative correlation between the proportion of choices of larger delayed rewards and net screen time (r = -0.25, p = 0.013), indicating that the more time is actively spent on a smartphone the less likely that individual is to wait for a larger award. The proportion of LDR choices was highly correlated (r = -0.98, p<0.001) with the natural logarithm of the discount parameter k according to Kirby et al. [15], indicating that the proportion measure was accurately assessing participants' discounting of future rewards. In line with this, the natural logarithm of k was also correlated with net screen time (r = 0.21, p = 0.034). However, we did not find a significant relationship between total screen time and delay discounting. Table 1 shows bivariate correlations between the main variables in this study (see also S2 Table for descriptive statistics and S1 Appendix for additional correlations).

Next, a regression analysis was performed to control for potential confounding variables in the relationship between net screen time and delay discounting (Table 2). In this analysis, we chose the LDR proportion (i.e. delay discounting) as the dependent variable without assuming a causal relationship between the two variables of interest. All assumptions for multiple regression were met. After controlling for demographic and psychological variables, net screen time was still a significant predictor of the LDR proportion (β = -0.24, p = 0.021), while all other independent variables were non-significant.

Delay discounting and usage by app category

As screen time data by application was available, we next sought to determine which components of net screen time predict delay discounting by performing a multiple regression with

Table 1. Correlations between main variables.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Net screen time	-										
2. Total screen time	0.94***	-									
3. Self-reported usage	0.56***	0.49***	-								
4. LDR proportion	-0.25*	-0.17	-0.23*	-							
5. ln overall k	0.21*	0.14	0.22*	-0.98***	-						
6. Self-control	-0.32**	-0.32**	-0.18	0.16	-0.14	-					
7. Consideration of future consequences	-0.17	-0.12	-0.12	0.07	-0.06	0.46**	-				
8. Response inhibition	0.00	-0.03	0.00	-0.19	0.22*	0.02	0.07	-			
9. Age	0.09	0.06	-0.13	0.05	-0.07	-0.05	0.06	-0.19	-		
10. Years of ownership	-0.04	-0.07	-0.08	0.11	-0.11	0.12	0.00	0.02	0.28	-	
11. Disposable income	-0.05	-0.07	0.06	-0.10	0.13	0.05	-0.09	0.05	0.14	0.12	-

*$p < 0.05$,

**$p < 0.01$,

*** $p < 0.001$.

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Table 2. Multiple regression analysis of predictors of LDR proportion.

Term	B	SE B	95% CI		β	t	p
			LL	UL			
Intercept	0.323	0.238	-0.149	0.795	0.000	1.359	0.178
Age	0.004	0.008	-0.011	0.020	0.079	0.571	0.569
Gender (Male)	0.035	0.018	-0.001	0.072	0.197	1.937	0.056
Education							
Hauptschulabschluss[a]	-0.195	0.153	-0.500	0.110	-0.281	-1.270	0.208
Fachabitur[b]	0.129	0.147	-0.164	0.422	0.186	0.872	0.385
Abitur[c]	0.046	0.057	-0.068	0.160	0.152	0.806	0.422
Bachelor	0.041	0.064	-0.086	0.169	0.116	0.646	0.520
Master/Diplom (Reference)							
Disposable income	0.000	0.000	0.000	0.000	-0.110	-1.065	0.290
Years of smartphone ownership	0.011	0.011	-0.012	0.033	0.102	0.954	0.343
Consideration of future consequences	0.000	0.003	-0.006	0.007	0.018	0.161	0.873
Self-control	0.001	0.003	-0.004	0.007	0.058	0.484	0.629
Response inhibition	-0.002	0.001	-0.004	0.001	-0.159	-1.542	0.127
Net screen time	-0.028	0.012	-0.053	-0.004	-0.243	-2.348	0.021

[a] German school leaving certificate awarded after 9th grade.

[b] German school certificate to enter University of Applied Sciences.

[c] German High School Diploma.

Note: Effect coding was applied for categorical variables.

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the proportion of LDR choices as the dependent variable and application categories as independent variables. Controlling for demographic and psychological variables, social media and gaming apps turned out to be significant predictors of delay discounting (β = -0.27, p = 0.009 and β = -0.25, p = 0.024, respectively). All other regressors were not significant as can be seen in the regression results in Table 3. We also performed a robustness check on our app categorization; for a second regression we added participants' YouTube screen time to the TV category instead of social media. Even with this adjustment social media and gaming apps remained significant, confirming these categories as predictors of delay discounting. The screen times of the most popular apps in our sample is shown in S3 Table.

Mediating role of self-control, response inhibition and consideration of future consequences

To investigate our second hypothesis, we initially examined the relationships of two psychological variables according to the model by Peters and Büchel [14] with actual smartphone usage and delay discounting. We found that self-control was negatively associated with net screen time (r = -0.32, p = 0.001), while all other relationships turned out to be non-significant at the 0.05-level (Table 1). We then performed mediation analyses using the PROCESS macro by Hayes [57]. This tool uses ordinary least squares regression, yielding path coefficients for total (i.e. between independent and dependent variable without mediator), direct (i.e. between independent and dependent variable with mediator), and indirect (i.e. through the mediator variable) effects. 5,000 bootstrap samples were constructed for each analysis to compute 95% confidence intervals and inferential statistics. Effects were deemed significantly different from zero when the confidence interval did not include zero. Three separate mediation analyses were performed to analyze whether self-control, response inhibition or consideration of future

Table 3. Multiple regression analysis of application categories.

Term	B	SE B	95% CI		β	t	p
			LL	UL			
Intercept	0.171	0.256	-0.338	0.680	0.000	0.668	0.506
Age	0.007	0.008	-0.009	0.024	0.133	0.884	0.379
Gender (Male)	0.028	0.018	-0.009	0.065	0.157	1.524	0.131
Education							
Hauptschulabschluss[a]	-0.263	0.151	-0.564	0.038	-0.380	-1.739	0.086
Fachabitur[b]	0.158	0.147	-0.135	0.450	0.228	1.073	0.286
Abitur[c]	0.072	0.058	-0.044	0.187	0.236	1.234	0.221
Bachelor	0.032	0.063	-0.094	0.158	0.090	0.505	0.615
Master/Diplom (Reference)							
Disposable income	0.000	0.000	0.000	0.000	-0.115	-1.108	0.271
Years of smartphone ownership	0.009	0.012	-0.014	0.033	0.090	0.807	0.422
Consideration of future consequences	0.000	0.003	-0.006	0.006	-0.005	-0.045	0.964
Self-control	0.003	0.003	-0.003	0.009	0.111	0.897	0.373
Response inhibition	-0.001	0.001	-0.003	0.001	-0.094	-0.881	0.381
Social Media	-0.044	0.017	-0.077	-0.011	-0.274	-2.676	0.009
Gaming	-0.087	0.038	-0.162	-0.012	-0.250	-2.300	0.024
Mail	-0.470	0.417	-1.299	0.360	-0.117	-1.126	0.263
Messenger	0.000	0.001	-0.002	0.002	0.005	0.051	0.960
Shopping	-0.034	0.147	-0.326	0.258	-0.024	-0.232	0.817
Browser	0.035	0.040	-0.045	0.115	0.090	0.864	0.390
Dating	0.051	0.068	-0.083	0.185	0.080	0.756	0.452
Other	0.127	0.071	-0.014	0.268	0.183	1.788	0.077

[a] German school leaving certificate awarded after 9th grade.

[b] German school certificate to enter University of Applied Sciences.

[c] German High School Diploma.

Note: Effect coding was applied for categorical variables.

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consequences could mediate the relationship between net screen time and delay discounting. We did not include reward responsiveness in the analyses, as the internal consistency of the scale was low. The indirect effects in all three models were non-significant (self-control B = -0.0032, CI [-0.0115, 0.0041]; response inhibition B = 0.0000, CI [-0.0051, 0.0042]; consideration of future consequences B = -0.0006, CI [-0.0049, 0.0034]). Compatibly, all direct effects remained significant, implying that neither self-control nor response inhibition nor consideration of future consequences played a mediating role in the relation between net screen time and delay discounting. Additional results of the mediation analyses are provided in S2 Appendix.

Self-reported vs. actual usage

Lastly, to compare self-reported usage patterns to actual usage we examined the relationships between net screen time and self-reports with regard to usage time, posting and checking behavior as well as reaction to notifications. We also investigated the association of self-reports to delay discounting.

Net screen time was moderately associated with self-reported usage time ($r = 0.56$, $p<0.001$). In a head-to-head comparison of self-reported vs. actual screen time we found that 71% of participants overestimated and 17% underestimated their screen time. For only 12% of participants, actual screen time fell into the usage interval (e.g. "1.5 to 2 hours per day on average") estimated by participants. Actual usage was also weakly related to checking behavior ($r = 0.21$, $p = 0.035$). When comparing self-reports to delay discounting, self-reported usage time and checking behavior were also associated with the LDR measure ($r = -0.23$, $p = 0.022$ and $r = -0.21$, $p = 0.036$, respectively). Reaction to notifications and posting behavior had no significant relationship neither to net screen time nor to the LDR measure.

Discussion

In this study we set out to investigate the relationship between actual smartphone usage and personal dispositions. Being a correlate of a host of maladaptive behaviors, the variable of delay discounting was of major interest. Consistent with previous studies investigating the association between delay discounting and smartphone usage primarily based on self-reports [18, 19, 35], we found a positive relationship between actual smartphone usage and the discounting of future rewards. Our results suggest that as smartphone screen time increases, the tendency to choose smaller immediate rewards over larger delayed rewards increases as well, confirming our first hypothesis. This association provides further empirical evidence that smartphone usage compares to other maladaptive behaviors, such as smoking, gambling or drinking in the context of intertemporal choice.

We were also able to identify two application categories which predicted delay discounting, namely social media and gaming apps. This result seems intuitive since both types of apps offer gratification in the form of likes or entertaining content (social media) and rewards or bonuses (gaming). Recent research showing that behavior on social media conforms to the principles of reward learning [58] lends initial support to this interpretation. Both app categories were also used extensively (46 minutes and 35 minutes per day on average, respectively), while social media were much more present on participants' phones than gaming apps (87% vs. 40% of phones). Interestingly, apps designed for shopping, a behavior shown to bear addiction potential [59], did not at all predict delay discounting. A possible explanation could be that online shopping was primarily done through other media, such as laptops or tablets—a hypothesis that is supported by the relatively short screen time of this app category (21 minutes per day on average). However, in interpreting these results it needs to be acknowledged that all application categories share similar mechanisms by sending notifications and quickly providing information, thereby involving gratification to some extent. More research is needed to uncover differences in the appeal of the various apps available to smartphone users.

When looking at the underlying mechanisms of delay discounting proposed by Peters and Büchel [14], we found that only self-control as assessed with the brief self-control scale was significantly correlated with net screen time; participants lower in self-control seemed to have greater difficulty in putting their phones aside than participants who reported to have higher self-control as observed in day-to-day behavior. This is in line with the finding of Wilmer and Chein [18] that heavier investment of time in a mobile device is related to weaker impulse control. However, our finding that the behavioral measure of self-control was not related to net screen time suggests that the cognitive process of response inhibition plays only a marginal role in how long a person engages with a smartphone. Interestingly, consideration of future consequences was neither associated with net screen time nor with delay discounting. On the one hand, this suggests that heavier smartphone users do not differ from lighter smartphone users in terms of the tendency to consider immediate vs. future outcomes of their day-to-day behaviors (as measured by the CFC scale). On the other hand, it seems that the CFC construct and delay discounting—despite their conceptual overlap—may not be used interchangeably when investigating their relationship with smartphone use.

We could not confirm our second hypothesis that the three psychological variables within the model of Peters and Büchel [14] mediate the relationship between smartphone screen time and delay discounting. This may indicate that smartphone usage has an idiosyncratic relationship with delay discounting, which cannot be explained with established concepts, namely self-control, response inhibition and consideration of future consequences. However, this preliminary conclusion needs further investigation, as we employed questionnaire-based and not neuroscientific methods (through which the model of interest has emerged) to assess the three psychological variables in this current study. Also, the possible mediating role of reward responsiveness has yet to be investigated. Moreover, for prospection we elicited a proxy variable, which might not have sufficient overlap with the concept proposed in the model of Peters and Büchel [14].

When comparing self-reports to actual usage data, we found that participants were able to estimate a general tendency of their screen time reasonably well. However, as expected these estimations were far from being accurate as indicated by the high percentage of under- and overestimations, suggesting that collecting actual data should be preferred whenever a high accuracy of data is required. This finding is in line with previous research highlighting the superiority of actual data in the context of smartphone usage [39].

These findings come with limitations, which may guide future research in the context of smartphone usage and its implications. First, we included only iPhone users in our sample, while users of other brands were not allowed to participate. While there is currently no reason to assume that smartphone usage differs systematically from iPhone to e.g. Samsung or Huawei phones, future studies should test our findings with other phone brands. Second, as restricted by the iOS feature participants' smartphone application data of the 7–10 days leading into the experiment was taken as a basis for their average use. While we did consider participants' comments about the "normality" of their latest usage patterns, using longer timeframes will result in more accurate data of user's typical screen time. Third, some inaccuracy is inherent in the browser application data. A web browser allows for a multitude of uses, which includes most of the other app categories investigated in this study. As we did not collect browsing history data, we were not able to determine what exactly our participants used their browser for, contributing to noisiness of the usage data. Fourth, the Monetary Choice Questionnaire employed in our study has several drawbacks. While it is very efficient, it is not the most sensitive instrument to assess delay discounting [60]. For instance, within the scale the smaller sooner option is always set to the present, thereby omitting intertemporal choices in which both rewards are available at different points in the future. This bears the risk of overweighing present bias in measuring delay discounting [61]. Furthermore, unusual discounters (i.e. participants with either negative or extremely high discount rates) cannot be captured with the Monetary Choice Questionnaire, as the scale only permits nine discrete discount rates between 0.00016 and 0.25 [62]. Future studies could employ e.g. computer-based, adjusting delay discounting tasks or even more general measures of time inconsistency as recently proposed e.g. by Rohde [63]. Lastly, all relationships reported in this study are correlational in nature, meaning that no inferences on causality can be made. Using our main finding as an example, enduring smartphone usage may cause an individual to become a more impulsive decision-maker over time. However, it is also possible that individual differences in the preference for immediate rewards result in investing more time in smartphone engagement. The latter relationship currently seems more likely, given the initial finding of Hadar et al. [35] that a three-month smartphone exposure did not cause any changes in impulsive decision-making, but more longitudinal research is needed.

Given the ever-growing role smartphones play in people's daily lives and the implied risk of overuse, it is crucial to understand individual differences which relate to smartphone usage. In this study, we provided further evidence for a behavioral similarity between smartphone usage and other maladaptive behaviors. Our findings suggest that especially heavy social media users and gamers should be mindful of their tendency to be drawn to smaller, immediate rewards. Alternatively, people who are already aware of their impulsive decision-making may benefit from the knowledge of their increased risk of overusing smartphones. These conclusions contribute to the view that smartphone use should not be underestimated but researched carefully to guide policy makers in shaping prudent use of this omnipresent technology.

Supporting information

S1 Table. Categorization of applications.
(DOCX)

S2 Table. Descriptive statistics for the main measures. Participants spent on average 3 hours and 12 minutes, at least 12 minutes and at most 8 hours and 24 minutes per day interacting with their smartphone. On average, the larger delayed reward was chosen 45% (minimum 7%, maximum 100%) of the time.
(DOCX)

S3 Table. Top 5 applications according to net screen time. Instagram was present almost on 75% of phones and had the highest average daily screen time of 46 minutes. The average net screen time per day is calculated over the number of phones on which the respective app was installed, so as to account for the prevalence of apps. 64% of participants used the YouTube app and spent on average 39 minutes per day engaging with it. This was followed by WhatsApp, which was installed by almost all participants, with an average screen time of 37 minutes.
(DOCX)

S1 Appendix. Additional correlations.
(DOCX)

S2 Appendix. Mediation diagrams.
(DOCX)

S1 Dataset. Raw data from the questionnaire and screen time data.
(XLSX)

S2 Dataset. Raw screen time data.
(XLSX)

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References

1. Taylor K, Silver L. Smartphone Ownership Is Growing Rapidly Around the World, but Not Always Equally. Pew Research Center; 2019 p. 3.
2. eMarketer. US Smartphone User Penetration, by Age, 2018 [Internet]. eMarketer. 2018 [cited 2020Mar26]. https://www.emarketer.com/chart/219283/us-smartphone-user-penetration-by-age-2018-of-population-each-group
3. Informate Mobile Intelligence. International Smartphone Mobility Report. Informate Mobile Intelligence; 2014.
4. Roberts J, Yaya L, Manolis C. The invisible addiction: Cell-phone activities and addiction among male and female college students. Journal of Behavioral Addictions. 2014 Aug 26; 3(4):254–65. https://doi.org/10.1556/JBA.3.2014.015 PMID: 25595966
5. Wigginton C, Curran M, Brodeur C. Global mobile consumer trends: second edition. Deloitte Touche Tohmatsu Limited; 2017.
6. Wilmer HH, Sherman LE, Chein JM. Smartphones and Cognition: A Review of Research Exploring the Links between Mobile Technology Habits and Cognitive Functioning. Frontiers in Psychology. 2017 Apr 25; 8.
7. Lin Y-H, Chang L-R, Lee Y-H, Tseng H-W, Kuo TBJ, Chen S-H. Development and Validation of the Smartphone Addiction Inventory (SPAI). PLoS ONE. 2014 Apr; 9(6).
8. Lin Y-H, Chiang C-L, Lin P-H, Chang L-R, Ko C-H, Lee Y-H, et al. Proposed Diagnostic Criteria for Smartphone Addiction. PloS One. 2016 Nov 15; 11(11). https://doi.org/10.1371/journal.pone.0163010 PMID: 27846211
9. Marty-Dugas J, Ralph BCW, Oakman JM, Smilek D. The relation between smartphone use and everyday inattention. Psychology of Consciousness: Theory, Research, and Practice. 2018; 5(1):46–62.
10. Ward AF, Duke K, Gneezy A, Bos MW. Brain Drain: The Mere Presence of One's Own Smartphone Reduces Available Cognitive Capacity. Journal of the Association for Consumer Research. 2017; 2 (2):140–54.
11. Barr N, Pennycook G, Stolz JA, Fugelsang JA. The brain in your pocket: Evidence that Smartphones are used to supplant thinking. Computers in Human Behavior. 2015; 48:473–80.
12. Madden GJ, Johnson PS. A delay-discounting primer. Impulsivity: The behavioral and neurological science of discounting. 2010:11–37.
13. Odum AL. Delay discounting: I'm a k, you're a k. Journal of the Experimental Analysis of Behavior. 2011 Nov; 96(3):427–39.
14. Peters J, Büchel C. The neural mechanisms of inter-temporal decision-making: understanding variability. Trends in Cognitive Sciences. 2011 May; 15(5):227–39. https://doi.org/10.1016/j.tics.2011.03.002 PMID: 21497544
15. Kirby KN, Petry NM, Bickel WK. Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. Journal of Experimental Psychology: General. 1999; 128(1):78–87. https://doi.org/10.1037//0096-3445.128.1.78 PMID: 10100392
16. Petry NM. Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls. Psychopharmacology. 2001 Mar 23; 154(3):243–50. https://doi.org/10.1007/s002130000638 PMID: 11351931
17. Dixon MR, Marley J, Jacobs EA. Delay Discounting By Pathological Gamblers. Journal of Applied Behavior Analysis. 2003 Feb 27; 36(4):449–58.
18. Wilmer HH, Chein JM. Mobile technology habits: patterns of association among device usage, intertemporal preference, impulse control, and reward sensitivity. Psychonomic Bulletin & Review. 2016 Mar 15; 23(5):1607–14.
19. Tang Z, Zhang H, Yan A, Qu C. Time Is Money: The Decision Making of Smartphone High Users in Gain and Loss Intertemporal Choice. Frontiers in Psychology. 2017 Mar 10; 8. https://doi.org/10.3389/fpsyg.2017.00363 PMID: 28344568
20. App Store [Internet]. Apple. [cited 2019Nov26]. https://www.apple.com/ios/app-store/
21. Android Apps on Google Play [Internet]. Google. Google; [cited 2019Nov26]. https://play.google.com/store/apps/
22. David ME, Roberts JA, Christenson B. Too Much of a Good Thing: Investigating the Association between Actual Smartphone Use and Individual Well-Being. International Journal of Human–Computer Interaction. 2017; 34(3):265–75.

23. Gower AD, Moreno MA. A Novel Approach to Evaluating Mobile Smartphone Screen Time for iPhones: Feasibility and Preliminary Findings. JMIR mHealth and uHealth. 2018; 6(11). https://doi.org/10.2196/11012 PMID: 30455163

24. Armstrong M. Infographic: 2018's Global Top 10 Android Apps [Internet]. Statista Infographics. Statista; 2019 [cited 2019Nov26]. https://www.statista.com/chart/16648/global-top-10-android-apps-2018/

25. Tamir DI, Mitchell JP. Disclosing information about the self is intrinsically rewarding. Proceedings of the National Academy of Sciences. 2012 Jul; 109(21):8038–43. https://doi.org/10.1073/pnas.1202129109 PMID: 22566617

26. Meshi D, Morawetz C, Heekeren HR. Nucleus accumbens response to gains in reputation for the self relative to gains for others predicts social media use. Frontiers in Human Neuroscience. 2013 Aug 29; 7. https://doi.org/10.3389/fnhum.2013.00439 PMID: 24009567

27. Sherman LE, Payton AA, Hernandez LM, Greenfield PM, Dapretto M. The Power of the Like in Adolescence. Psychological Science. 2016; 27(7):1027–35. https://doi.org/10.1177/0956797616645673 PMID: 27247125

28. Koepp MJ, Gunn RN, Lawrence AD, Cunningham VJ, Dagher A, Jones T, et al. Evidence for striatal dopamine release during a video game. Nature. 1998 May 21; 393(6682):266–8. https://doi.org/10.1038/30498 PMID: 9607763

29. Kühn S, Romanowski A, Schilling C, Lorenz R, Mörsen C, Seiferth N, et al. The neural basis of video gaming. Translational Psychiatry. 2011 Nov; 1(11) https://doi.org/10.1038/tp.2011.53 PMID: 22833208

30. Lanaj K, Johnson RE, Barnes CM. Beginning the Workday Already Depleted? Consequences of Late-Night Smartphone Use and Sleep Quantity. Academy of Management Proceedings. 2012; 2012 (1):14372.

31. Vahedi Z, Saiphoo A. The association between smartphone use, stress, and anxiety: A meta-analytic review. Stress and Health. 2018; 34(3):347–58. https://doi.org/10.1002/smi.2805 PMID: 29673047

32. Samaha M, Hawi NS. Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. Computers in Human Behavior. 2016; 57:321–5.

33. Rotondi V, Stanca L, Tomasuolo M. Connecting alone: Smartphone use, quality of social interactions and well-being. Journal of Economic Psychology. 2017; 63:17–26.

34. Delaney D, Stein LAR, Gruber R. Facebook addiction and impulsive decision-making. Addiction Research & Theory. 2017 Nov 27; 26(6):478–86.

35. Hadar A, Hadas I, Lazarovits A, Alyagon U, Eliraz D, Zangen A. Answering the missed call: Initial exploration of cognitive and electrophysiological changes associated with smartphone use and abuse. PloS One. 2017 Jul 5; 12(7). https://doi.org/10.1371/journal.pone.0180094 PMID: 28678870

36. Kwon M, Lee J-Y, Won W-Y, Park J-W, Min J-A, Hahn C, et al. Development and Validation of a Smartphone Addiction Scale (SAS). PLoS ONE. 2013 Dec 27; 8(12).

37. Kobayashi T, Boase J. No Such Effect? The Implications of Measurement Error in Self-Report Measures of Mobile Communication Use. Communication Methods and Measures. 2012 Jun 8; 6(2):126–43.

38. Boase J, Ling R. Measuring Mobile Phone Use: Self-Report Versus Log Data. Journal of Computer-Mediated Communication. 2013 Jul 1; 18(4):508–19.

39. Andrews S, Ellis DA, Shaw H, Piwek L. Beyond Self-Report: Tools to Compare Estimated and Real-World Smartphone Use. PloS One. 2015 Oct 28; 10(10). https://doi.org/10.1371/journal.pone.0139004 PMID: 26509895

40. Bianchi A, Phillips JG. Psychological Predictors of Problem Mobile Phone Use. CyberPsychology & Behavior. 2005 Feb 28; 8(1):39–51. https://doi.org/10.1089/cpb.2005.8.39 PMID: 15738692

41. Greiner B. Subject pool recruitment procedures: organizing experiments with ORSEE. Journal of the Economic Science Association. 2015 May 7; 1(1):114–25.

42. Epstein LH, Richards JB, Saad FG, Paluch RA, Roemmich JN, Lerman C. Comparison between two measures of delay discounting in smokers. Experimental and Clinical Psychopharmacology. 2003; 11 (2):131–8. https://doi.org/10.1037/1064-1297.11.2.131 PMID: 12755457

43. Lagorio CH, Madden GJ. Delay discounting of real and hypothetical rewards III: Steady-state assessments, forced-choice trials, and all real rewards. Behavioural Processes. 2005 May 31; 69(2):173–87.

44. Myerson J, Baumann AA, Green L. Discounting of delayed rewards: (A)theoretical interpretation of the Kirby questionnaire. Behavioural Processes. 2014 Sep; 107:99–105. https://doi.org/10.1016/j.beproc.2014.07.021 PMID: 25139835

45. Kaplan BA, Lemley SM, Reed DD, Jarmolowicz DP. 21- and 27-Item Monetary Choice Questionnaire Automated Scorer [software]. 2014. http://hdl.handle.net/1808/15424

46. Kaplan BA, Amlung M, Reed DD, Jarmolowicz DP, Mckerchar TL, Lemley SM. Automating Scoring of Delay Discounting for the 21- and 27-Item Monetary Choice Questionnaires. The Behavior Analyst. 2016 Aug 19; 39(2):293–304. https://doi.org/10.1007/s40614-016-0070-9 PMID: 31976983

47. Carver CS, White TL. Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS Scales. Journal of Personality and Social Psychology. 1994 Aug; 67(2):319–33.

48. Strobel A, Beauducel A, Debener S, Brocke B. Eine deutschsprachige Version des BIS/BAS-Fragebogens von Carver und White. Zeitschrift für Differentielle und Diagnostische Psychologie. 2001; 22 (3):216–27.

49. Robinson MD, Schmeichel BJ, Inzlicht M. A Cognitive Control Perspective of Self-Control Strength and Its Depletion. Social and Personality Psychology Compass. 2010; 4(3):189–200.

50. Bertrams A, Dickhäuser O. Messung dispositioneller selbstkontroll-kapazität: eine deutsche adaptation der kurzform der self-control scale (SCS-KD). Diagnostica. 2009 Jan; 55(1):2–10.

51. Tangney JP, Baumeister RF, Boone AL. High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. Journal of Personality. 2004; 72(2):271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x PMID: 15016066

52. Mostofsky SH, Schafer JG, Abrams MT, Goldberg MC, Flower AA, Boyce A, et al. fMRI evidence that the neural basis of response inhibition is task-dependent. Cognitive Brain Research. 2003 Jul 15; 17 (2):419–30. https://doi.org/10.1016/s0926-6410(03)00144-7 PMID: 12880912

53. Strathman A, Gleicher F, Boninger DS, Edwards CS. The consideration of future consequences: Weighing immediate and distant outcomes of behavior. Journal of Personality and Social Psychology. 1994; 66(4):742–52.

54. Teuscher U, Mitchell SH. Relation between time perspective and delay discounting: A literature review. The Psychological Record. 2011 Oct 1; 61(4):613–32.

55. Atance CM, Oneill DK. Episodic future thinking. Trends in Cognitive Sciences. 2001 Dec 1; 5(12):533–9. https://doi.org/10.1016/s1364-6613(00)01804-0 PMID: 11728911

56. Bruderer Enzler H. Consideration of Future Consequences as a Predictor of Environmentally Responsible Behavior. Environment and Behavior. 2013 Nov 28; 47(6):618–43.

57. Hayes AF. PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. 2012. http://www.afhayes.com/public/process2012.pdf

58. Lindström B, Bellander M, Chang A, Tobler PN, Amodio DM. A computational reinforcement learning account of social media engagement. [Preprint]. PsyArXiv; 2019. psyarxiv.com/78mh5

59. Hartston H. The Case for Compulsive Shopping as an Addiction. Journal of Psychoactive Drugs. 2012 Jan; 44(1):64–7. https://doi.org/10.1080/02791072.2012.660110 PMID: 22641966

60. Matta AD, Gonçalves FL, Bizarro L. Delay discounting: Concepts and measures. Psychology & Neuroscience. 2012 Dec 28; 5(2):135–46.

61. O'Donoghue T, Rabin M. Present bias: Lessons learned and to be learned. American Economic Review. 2015 May; 105(5):273–79.

62. Towe SL, Hobkirk AL, Ye DG, Meade CS. Adaptation of the Monetary Choice Questionnaire to accommodate extreme monetary discounting in cocaine users. Psychology of Addictive Behaviors. 2015 Dec; 29(4):1048. https://doi.org/10.1037/adb0000101 PMID: 26191820

63. Rohde KI. Measuring decreasing and increasing impatience. Management Science. 2019 Apr; 65 (4):1700–16.

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RESEARCH ARTICLE

Addictive use of digital devices in young children: Associations with delay discounting, self-control and academic performance

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Abstract

The use of smartphones, tablets and laptops/PCs has become ingrained in adults' and increasingly in children's lives, which has sparked a debate about the risk of addiction to digital devices. Previous research has linked specific use of digital devices (e.g. online gaming, smartphone screen time) with impulsive behavior in the context of intertemporal choice among adolescents and adults. However, not much is known about children's addictive behavior towards digital devices and its relationship to personality factors and academic performance. This study investigated the associations between addictive use of digital devices, self-reported usage duration, delay discounting, self-control and academic success in children aged 10 to 13. Addictive use of digital devices was positively related to delay discounting, but self-control confounded the relationship between the two variables. Furthermore, self-control and self-reported usage duration but not the degree of addictive use predicted the most recent grade average. These findings indicate that children's problematic behavior towards digital devices compares to other maladaptive behaviors (e.g. substance abuse, pathological gambling) in terms of impulsive choice and point towards the key role self-control seems to play in lowering a potential risk of digital addiction.

Introduction

Digital devices, such as smartphones, tablets and laptops, have become an integral part in the lives of the majority of people around the world. Recent surveys e.g. in the US estimate that 81% of adults own a smartphone, 74% own a laptop and 52% own a tablet [1]. Notably, not only adults but also children have been increasingly surrounded by digital devices; a report from the UK states that in 2019 more than two thirds of 5- to 16-year-olds owned a smartphone and that 80% of 7- to 16-year-olds had internet access in their own room [2]. The same report also estimates that children's average time spent online is 3.4 hours per day, with the main activities being watching videos (e.g. on YouTube and TikTok), using social media (e.g. Instagram and Snapchat) or gaming (e.g. Fortnite or Minecraft). These numbers have seen an unprecedented increase since the COVID-19 pandemic, which has, to a large extent, forced children to remain home, receive online schooling and interact with friends digitally. While the effects of these measures vary from country to country, a 163% increase in daily screen

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time during the first lockdown in Germany is not an unusual occurrence as observed by Schmidt et al. [3].

These developments have added momentum to the debate about the addiction potential of digital devices—especially for children, who are particularly at risk of developing addictive behaviors [4]. Evidence of negative implications of excessive digital device use, such as stress [5], sleep disturbance [6] or poor academic performance [7], has accumulated in recent years. However, researchers have not yet agreed on a standardized definition of digital addiction, which clearly separates it from other, possibly underlying disorders [8]. For one aspect of problematic use of digital devices, namely Internet Gaming Disorder, existing research has matured to stage where it suggests a potential future inclusion in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), as an officially diagnosable condition. Other aspects, such as smartphone addiction, are less mature and the literature has so far only identified a significant overlap between addiction to smartphones and substance-related disorders defined in the DSM-5 [9, 10]. One area of research, which seeks to explore overall addiction to digital devices, encompassing various media (e.g. smartphones, tablets and laptops/PCs) and activities (e.g. gaming, social media), seems promising but is still in its infancy [11]. Unlike the aforementioned strands of literature, research on overall digital addiction takes into account the newly emerged usage behavior of performing a multitude of activities on and across several different digital devices (e.g. sending WhatsApp messages on a smartphone, playing games on a tablet and watching movies on a laptop). This may promote a degree of consolidation of the large number of concepts of technology addiction and their corresponding scales, which have emerged over the years but have recently been shown to be highly similar on a dimensional level [12].

A scale assessing digital addiction particularly among young children was recently introduced [11]. The Digital Addiction Scale for Children (DASC) measures to which degree children's use of smartphones, tablets and laptops/PCs negatively affects their educational, psychological, social and physical well-being. To account for the ongoing debate about a standardized definition of digital addiction and the corresponding lack of a firm diagnosis, throughout this paper the softer formulation "addictive use of digital devices" is used rather than "digital addiction" when referring to children's use of digital devices with adverse consequences. To further our understanding of this behavioral pattern and enable possible future intervention, the scale needs to be investigated in connection with personality factors, which may contribute to problematic behavior towards digital devices [13].

In this context, delay discounting, i.e. the tendency to discount rewards as a function of the delay of their delivery, suggests itself as an avenue for research. This cognitive process underlies human and non-human animals' preference for smaller, immediate rewards over larger, delayed rewards and is often used as a measure of impulsivity [14]. Delay discounting has been studied extensively in the past decades, mostly by means of intertemporal choice problems, in which participants are faced with the tradeoff between the amount and the delay of a reward (e.g. choosing between 100€ today or 150€ in one month). Several models seeking to capture behavior have emerged, with hyperbolic discounting providing the best fit for most empirical data [15]. Its equation $V = A / (1+kD)$ (V is the present value of the future reward, A is the reward amount and D is the delay to the reward) contains one free parameter k, which represents an individual's discount rate. The lower this discounting parameter, the less the individual devalues future rewards and is therefore relatively less impulsive than a person with a higher discount rate. Due to the relative temporal stability of individuals' discount rates, delay discounting may be seen as a trait variable [16]. Also, a plethora of studies has shown an association between delay discounting and a variety of maladaptive behaviors, such as substance abuse [17], smoking [18] and pathological gambling [19, 20] or overeating [21]. In these studies, addicted individuals discounted future rewards more steeply than control subjects, which makes delay discounting a reliable indicator for various kinds of addictions [22]. Given that the discounting of future rewards is not only related to substance-based but also to behavioral addictions, this raises the question if delay discounting is also associated with addictive use of digital devices. Past studies have only been able to show relationships between delay discounting and single aspects of digital use, such as internet gaming [23] or smartphone screen time [24]. In addition, the samples studied consisted of adolescents or adults, despite regular use of digital devices already starting in childhood [2].

Furthermore, researchers agree on the key role of self-control in the development [25] and treatment [26] of addictive behaviors. On the one hand, a decreased ability to regulate thoughts and emotions contributes to risk-taking behavior, such as initiating use of addictive drugs, which is a common phenomenon in adolescents [27]. On the other hand, impaired self-control is a key symptom of addicted individuals, i.e. the inability to stop engaging in addictive behavior despite a willingness to do so. Thus, behavioral training to strengthen control functions has been proposed as an effective approach to reduce addiction [28]. Additionally, prominent models of decision-making have also highlighted self-control as a mechanism underlying delay discounting [22, 29]. According to these accounts, exertion of self-control suppresses the impulse of choosing a smaller, immediate reward and biases choice behavior towards the larger, delayed reward. However, the interrelationships between delay discounting, addictive use of digital devices and self-control have yet to be explored.

Lastly, a number of studies have shown an association between various kinds of addictive behavior and poor academic performance [30–32]. Being distracted in the classroom or while studying, concentration lapses due to lack of sleep or missing classes and exams have been put forth as explanations for this finding. Given the novelty of the concept of digital addiction, the question whether the pattern suggested by the literature also holds in the context of addictive use of digital devices, particularly by young children, needs empirical investigation. This issue is of great importance as fundamental reading, writing and mathematics skills are taught at this stage. It is also relevant for the debate about increasingly integrating digital media in classroom activities and homework as part of the digitalization of schools. Therefore, this present study examines the following three hypotheses:

H1: Delay discounting is positively correlated with children's addictive use of digital devices

H2: Self-control is negatively correlated with children's addictive use of digital devices

H3: Children's addictive use of digital devices is negatively correlated with academic success

This study contributes to the literature by showing behavioral similarities between addictive use of digital devices and other problematic behaviors, by highlighting the central role that self-control seems to play in the context of digital addiction and by uncovering an intriguing pattern when comparing the relationships of problematic use vs. raw usage duration of digital devices with academic success.

Methods

Participants

75 children aged 10 to 13 (mean 11.3 years, 47% female) with no officially diagnosed mental disorders (e.g. Attention-Deficit/Hyperactivity Disorder, Obsessive-Compulsive Disorder) were recruited from a public elementary school in Berlin, Germany. The participants were 5th and 6th grade students and were selected for two reasons. On the one hand, participants needed to be able to understand the tasks and questionnaires employed in this study. On the

other hand, this age represents a major crossroad for the children of Berlin; within the city's school system, students graduate from elementary school after 6th grade and progress to either high school ("Gymnasium") or integrative secondary school ("Integrierte Sekundarschule") depending on their academic performance (a German high school diploma provides eligibility to attend University, while students from Integrative Secondary School graduate after 9th or 10th grade in order to start an apprenticeship). This age group, prior to above-mentioned separation, thus had the positive side effect of implying a variety of academic skills as well as socio-economic backgrounds. Furthermore, the school's headmaster affirmed that there was a significant diversity of ethnicities and nationalities among students and that no mental disorders existed in the observed classes. Parents (or guardians) of all participants were informed that participation was voluntary as well as anonymous and did not have an impact on their children's grades. Roughly 15% of invited students chose not to participate in the study. Informed consent documents were signed before each study session.

Measures

Addictive use of digital devices. To measure the degree of addictive use of smartphones and tablets the Digital Addiction Scale for Children (DASC) [11] was employed. The DASC is a 25-item self-report instrument based on the theoretical framework of DSM-5 Internet Gaming Disorder as well as on the components model of addiction [33]. The resulting nine addiction criteria are Preoccupation, Tolerance, Withdrawal, Problems, Conflict, Deception, Displacement, Relapse and Mood Modification, each represented by two to four items within the scale. Scores range from 25 to 125, higher scores indicating a greater risk of addiction to digital devices. As only the degree of smartphone and tablet use with adverse consequences rather than the identification of addicts was relevant to this study, the scale was not used to distinguish between addicts and non-addicts in the analyses. Correspondingly, throughout this paper the formulation "addictive use of digital devices" is used rather than "digital addiction", to avoid suggesting a firm diagnosis, which is not available at the moment. The scale was specifically developed for 9- to 12-year-old children and has been shown to be a reliable and valid instrument to assess the risk of being addicted to digital devices [11]. A German translation of the DASC was used, after having been checked for understandability by one 5th grade and one 6th grade teacher independently. The internal consistency of the scale was excellent ($\alpha = 0.94$).

Delay discounting. The participants' preference for smaller immediate rewards over larger delayed rewards was assessed with a German translation of the 27-item Monetary Choice Questionnaire [17]. In this questionnaire participants repeatedly choose between a smaller, immediately available reward and a larger reward available in the future, all rewards being hypothetical and consisting of small (e.g. €20), medium (e.g. €54) and large amounts of money (e.g. €78). The proportion of choices of the larger delayed reward (LDR) is used as a measure of impulsivity, i.e. the lower the proportion, the more impulsive the individual. The scale is widely used in the literature for studying adults and has also been shown to be a valid instrument for young children [34–36]. Also, the Monetary Choice Questionnaire provides similar results to more extended instruments [37] as well as to paradigms that use real or potentially real rewards [38]. Furthermore, the proportion of LDR measure is a simple yet reliable and valid measure, which does not require the assumption of hyperbolic discounting [39]. Within the present dataset the LDR proportion was highly correlated ($r = -0.98$, $p<0.001$) with the natural log of the discount parameter k according to Kirby et al. [17], indicating that the LDR measure was accurately assessing participants' discounting of future rewards. The responses to the Monetary Choice Questionnaire were scored using automated scoring [40]. This tool also provides consistency scores in order to identify insufficient comprehension or a lack of or attending to the questionnaire. Three participants had consistency scores below 75%, the recommended threshold for good quality of responses [41], resulting in their exclusion from the analyses.

Self-control. As a measure of self-control the German adaptation [42] of Tangney et al.'s Brief Self-Control Scale [43] was used, which is a widely used self-report measure of trait self-control. Scores range from 13 to 65, higher scores representing better ability to regulate thoughts, emotions and behavior. Research has shown that the 13-item brief self-control scale provides equally reliable and valid results as the long version [43] and is appropriate for use with young children [44]. Good internal consistency was indicated by Cronbach's α of 0.75.

Additional variables. As a measure of academic performance, the most recent semester's grade average with a possible range from 1.0 (best possible, "straight A") to 6.0 (worst possible, "straight F") was used. Also, children were asked to estimate their average daily duration of several popular activities on digital devices (e.g. social media, games) as well as their typical total screen time on weekdays and weekends to attain various measures for self-reported usage, thereby allowing for robustness checks of results. Lastly, age, gender, years of smartphone ownership and weekly pocket money were elicited as control variables.

Procedure

Data was collected in June 2020, several weeks after reopening of schools following the initial seven-week lockdown in Germany. The study was conducted in five sessions, which were held in the school's computer lab. At the beginning of each session, the researcher instructed participants about the tasks, while a teacher assisted in ensuring a setting comparable to class examination (silence, no copying from neighbors etc.). Throughout all sessions the order of tasks was fixed as follows: 1) self-reported usage patterns, 2) Monetary Choice Questionnaire, 3) Digital Addiction Scale, 4) control variables and 5) Brief Self-Control scale. One session lasted about 30 minutes. The study was approved by the Central Ethics Committee of the Freie Universität Berlin (approval no. 2020–005)

Results

Addictive use of digital devices and delay discounting

To investigate the first hypothesis, initially the relationship between scores of the DASC and the LDR proportion was analyzed. A negative correlation ($r = -0.28$, $p = 0.016$) between the two variables was found. On average, the more often children chose the larger delayed reward, the less they addictively used digital devices. When breaking down the DASC into its nine subscales, delay discounting was significantly correlated with Withdrawal ($r = 0.30$, $p = 0.014$), Deception ($r = 0.24$, $p = 0.043$) and Mood Modification ($r = 0.29$, $p = 0.010$). Next, to control for possible effects of gender, age, years of ownership of digital devices and pocket money a regression analysis was performed with the control variables and the proportion of LDR choices as independent variables and the overall DASC score as the dependent variable. All assumptions for multiple regression analysis were met. As shown in Table 1, the LDR proportion was the only significant predictor of scores in the DASC ($\beta = -0.27$, $p = 0.032$). The overall model yielded an R^2 of 0.10, F-statistic of 1.50 and p-value of 0.201. The similarity in correlation patterns of the natural log of the discount parameter k and the LDR proportion indicated that the latter measure was accurately assessing participants' delay discounting. Additionally, self-reported usage of digital devices was positively correlated to the DASC score ($r = 0.37$, $p = 0.001$), but no relationship was found with delay discounting ($r = 0.09$, $p = 0.465$). Self-reported usage was positively related to the DASC subscales Preoccupation, Withdrawal, Displacement, Relapse and Problems, the latter showing the strongest correlation of $r = 0.41$

Table 1. Multiple regression analysis of predictors of DASC score.

Term	B	SE B	95% CI		β	t	p
			LL	UL			
Intercept	85.41	24.62	36.25	134.56	0.00	3.47	0.001
Age	-2.26	2.25	-6.74	2.22	-0.12	-1.01	0.318
Gender (Male)	1.26	2.09	-2.92	5.44	0.07	0.60	0.550
Pocket money	-0.06	0.19	-0.43	0.31	-0.04	-0.32	0.748
Years of ownership	0.21	1.62	-3.03	3.44	0.02	0.13	0.899
LDR proportion	-18.08	8.23	-34.51	-1.65	-0.27	-2.20	0.032

Note: Effect coding was applied for categorical variables.

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($p<0.001$). Table 2 shows bivariate correlations of the main variables in this study. The breakdown of the DASC and its correlations with key variables can be found in S2 Table.

Addictive use of digital devices and self-control

The second hypothesis required an investigation of the relationship between addictive digital device use and self-control. There was a strong negative correlation between self-control and the DASC score ($r = -0.69$, $p<0.001$). On average, the higher children's scores were on the brief self-control scale the less they tended to addictively use digital devices. Correspondingly, self-control was negatively associated with all nine subscales of the DASC, having the strongest relationship with Tolerance ($r = -0.65$, $p<0.001$). Furthermore, self-control was also correlated to the LDR proportion ($r = 0.25$, $p = 0.034$), indicating possible confounding between addictive behavior and delay discounting. Therefore, a regression analysis was performed with the control variables (gender, age, years of ownership of digital devices and pocket money), self-reported usage, self-control as well as the proportion of LDR choices as independent variables and the overall DASC score as the dependent variable. As displayed in Table 3, self-control ($\beta = -0.58$, $p<0.001$) and self-reported usage ($\beta = 0.32$, $p = 0.003$) were the only significant predictors of the DASC score. Notably, with the variable self-control in the model the LDR proportion no longer significantly predicted the DASC score ($\beta = -0.15$, $p = 0.100$). The overall model's R^2 was 0.59 with an F-statistic of 13.21 and p-value of <0.001.

Table 2. Correlations between main variables.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. DASC score	-								
2. Self-reported usage	0.37**	-							
3. LDR proportion	-0.28*	0.09	-						
4. ln overall k	0.27*	-0.07	-0.98***	-					
5. Self-control	-0.69***	-0.20	0.25*	-0.23*	-				
6. Grade average	0.15	0.43***	0.02	-0.03	-0.31*	-			
7. Age	-0.16	0.09	0.12	-0.11	0.06	0.21	-		
8. Years of ownership	0.00	0.36**	-0.06	0.07	0.12	0.16	0.22	-	
9. Pocket money	0.00	0.43***	-0.19	0.20	0.11	0.10	0.10	0.25*	-

$^{*}p < 0.05$
$^{**}p < 0.01$
$^{***}p < 0.001$.

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Table 3. Multiple regression analysis of predictors of DASC score.

Term	B	SE B	95% CI		β	t	p
			LL	UL			
Intercept	123.12	18.94	85.28	160.95	0.00	6.50	< .0001
Age	-2.18	1.54	-5.26	0.90	-0.12	-1.41	0.162
Gender (Male)	2.24	1.46	-0.68	5.15	0.13	1.53	0.130
Pocket money	-0.12	0.15	-0.42	0.17	-0.08	-0.82	0.415
Years of ownership	-0.21	1.20	-2.60	2.18	-0.02	-0.18	0.860
LDR proportion	-10.47	6.27	-23.00	2.05	-0.15	-1.67	0.100
Self-control	-1.18	0.19	-1.56	-0.80	-0.58	-6.19	< .0001
Self-reported usage	1.18	0.38	0.42	1.94	0.32	3.10	0.003

Note: Effect coding was applied for categorical variables.

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Addictive use of digital devices and academic success

Lastly, for hypothesis 3 the relationship between addictive use of digital devices and performance in the classroom was examined. The DASC scores and grade averages were not correlated ($r = 0.15$, $p = 0.197$). However, there was a positive correlation between self-reported usage of digital devices and grade average ($r = 0.43$, $p<0.001$). On average, the more time was reportedly spent with digital devices the worse the academic performance. Furthermore, self-control was also correlated to academic success ($r = -0.31$ $p = 0.007$). Again, to take into account possible effects of gender, age, years of ownership of digital devices and pocket money a regression analysis with the latter variables, self-control and self-reported usage predicting grade average was performed. As displayed in Table 4, self-control ($\beta = -0.30$, $p = 0.009$) and self-reported usage ($\beta = 0.26$, $p = 0.040$) were the only significant predictors of grade average. R^2 of the overall model was 0.31 with an F-statistic of 4.89 and $p < 0.001$. See S1 Appendix for robustness checks related to self-reported usage.

Discussion

The main goal of this present study was to investigate the relationship between children's addictive use of digital devices and delay discounting. Consistent with previous studies on more established addictive behaviors among adolescents and adults (e.g. substance abuse, gambling, smoking), children who discounted future rewards more heavily tended to more addictively use smartphones, tablets and computers. Children showing more addictive use

Table 4. Multiple regression analysis of predictors of grade average.

Term	B	SE B	95% CI		β	t	p
			LL	UL			
Intercept	1.21	0.99	-0.77	3.19	0.00	1.22	0.226
Age	0.14	0.08	-0.03	0.30	0.18	1.68	0.098
Gender (Male)	0.00	0.08	-0.15	0.15	0.00	-0.02	0.983
Pocket money	0.01	0.01	0.00	0.03	0.21	1.81	0.075
Years of ownership	0.00	0.06	-0.12	0.13	0.01	0.07	0.947
Self-reported usage	0.04	0.02	0.00	0.08	0.26	2.1	0.040
Self-control	-0.02	0.01	-0.04	-0.01	-0.30	-2.68	0.009

Note: Effect coding was applied for categorical variables.

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seem to be drawn to the immediate rewards of watching videos, gaming or social media in spite of negative long-term consequences of that behavior. The implications of this finding are twofold. First, digital addiction as a fairly new concept compares to other problematic behaviors in the context of delay discounting, suggesting its further investigation as a potentially diagnosable addiction in the future. Second, children as young as ten years old may show problematic behavior towards digital devices which has previously been observed only in adolescents and adults.

Another question addressed by this study was which role self-control played in the relationship between delay discounting and addictive use of digital devices. The regression analysis yielded that self-control confounded the relationship between the two main variables, implying that steeper discounters tended to more addictive use of digital devices due to differences in self-control. The present data suggest that children's ability to control thoughts and emotions is the mechanism underlying the association between delay discounting and addictive use and thus is a superior predictor of problematic behavior towards digital devices. Existing studies focusing on smartphone use and delay discounting found mixed results on a mediating role of self-control (mediation see Wilmer & Chein [45], no mediation see Schulz van Endert & Mohr [24]). Due to the cross-sectional and observational nature of the data, no conclusion with regard to mediation can be made in this present study [46]. Nonetheless, the moderate to strong association between self-control and addictive digital device usage found in this present study at least indicates that children who are better able to regulate thoughts and emotions tend to show a lower degree of addictive use of smartphones, tablets etc. Although the present data do not allow for firm conclusions on the direction of causality, it seems that self-controlled children resist the temptation of continued engagement with digital devices before negative effects (conflict, mood modification etc.) occur. Children lower in self-control on the other hand seem to be less able to refrain from gaming, watching videos or chatting despite recognizing adverse consequences of that behavior. Considering previous findings on the positive effect of self-control training on preventing internet addiction [47], the present finding hints at the importance of developing children's self-control in order to lower the risk of developing addictive behaviors towards digital devices.

The third association of interest was that of addictive digital device use and academic performance. Based on previous findings with other problematic behaviors, a negative relationship between these two variables was hypothesized. However, no significant association was found in this current study. Instead, self-reported usage turned out to be a significant predictor of grade average; the longer children reported to use digital devices the worse their grade average tended to be. This pattern of results suggests that children need not show symptoms of addiction, but that screen time alone may already implicate lower academic achievement. The latter finding is in line with related studies which investigated the relationship between smartphone use and students' academic success [48]. The classical interpretation for this result is that more screen time implies less study time, which leads to worse classroom performance. However, due to the correlational nature of results in this current study, the opposite causal direction cannot be ruled out. Last but not least, in line with previous large-scale studies [43, 44], self-control was found to be a significant predictor of academic success. This highlights once more the key role of children's self-control in achieving better grades already in elementary school.

The findings of this study need to be seen in light of several limitations. First, despite the (partially highly) significant results, the sample was limited in size and stemmed from one elementary school. Future studies should investigate samples from different cities and countries to allow for higher generalizability of results. Second, key variables (addictive use of digital devices, self-control, usage duration of digital devices) in this study were elicited using self-report questionnaires. While this method is standard practice in fields such as addiction or personality research, self-estimations of screen time have been shown to diverge from actual data [49]–a phenomenon which is likely amplified due to the young age of participants. To reduce response biases, future studies might include additional sources of reports (e.g. parents, teachers or peers) or even actual screen time data, as shown in e.g. Schulz van Endert & Mohr [24]. Third, due its novelty the DASC has not yet undergone extensive validation yet. Recent research has highlighted the importance of repeated validation of psychometric scales [50, 51], which is why the results of the DASC should be interpreted tentatively at this stage. Fourth, the Monetary Choice Questionnaire is an efficient but—compared to more extensive alternatives—less sensitive instrument to assess delay discounting [52]. For example, it does not include intertemporal choices in which both rewards are given at different points in the future, which bears the risk of overweighting present bias [53]. Alternatively, adjusting delay discounting tasks, e.g. as proposed by Koffarnus & Bickel [54], could be used in future studies. Fifth, this study presented correlational results, which do not allow for causal interpretations. Looking at the reported association between self-control and addictive use of digital devices, one cannot determine using the present data whether a lack of self-control causes more addictive use or whether more problematic engagement with digital devices decreases self-control. Such conclusions may only be drawn from longitudinal or experimental studies, which are greatly needed in the future.

This study highlighted the importance of studying and monitoring the use of digital devices in children as early as at elementary school level. 10- to 13-year-olds may already show problematic behavioral patterns which have so far been only observed in older individuals. Furthermore, the central role of self-control in the context of addictive behavior as well as academic success was further underlined in this study. As experiences and influences in childhood greatly impact the trajectory of a person's entire life, researchers, politicians, educators and parents/guardians are well-advised to closely observe the impact of omnipresent digital devices on children and to assist in the development of traits which promote their well-being in the present and in the future.

Supporting information

S1 Table. Descriptive statistics of key variables.
(DOCX)

S2 Table. Correlations between DASC subscales and key variables.
(DOCX)

S1 Appendix. Additional correlations.
(DOCX)

S2 Appendix. Mediation analysis.
(DOCX)

S1 Dataset. Raw data from the questionnaires.
(XLSX)

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References

1. Mobile Fact Sheet [Internet]. Pew Research Center; 2020 [cited 2021Jan28]. Available from: https://www.pewresearch.org/internet/fact-sheet/mobile/.
2. Monitor Report 2020. CHILDWISE; 2020 [cited 2021Jan28]. Available from: http://www.childwise.co.uk/monitor.html.
3. Schmidt S, Anedda B, Burchartz A, Eichsteller A, Kolb S, Nigg C, et al. Physical activity and screen time of children and adolescents before and during the COVID-19 lockdown in Germany: a natural experiment. Scientific Reports. 2020; 10(1). 12. https://doi.org/10.1038/s41598-019-55410-5 PMID: 31913299
4. Spear L. The adolescent brain and age-related behavioral manifestations. Neuroscience & Biobehavioral Reviews. 2000; 24(4):417–463. https://doi.org/10.1016/s0149-7634(00)00014-2 PMID: 10817843
5. Chiu S. The relationship between life stress and smartphone addiction on taiwanese university student: A mediation model of learning self-Efficacy and social self-Efficacy. Computers in Human Behavior. 2014; 34:49–57.
6. Thomée S, Härenstam A, Hagberg M. Mobile phone use and stress, sleep disturbances, and symptoms of depression among young adults—a prospective cohort study. BMC Public Health. 2011; 11(1).
7. Hawi N, Samaha M. To excel or not to excel: Strong evidence on the adverse effect of smartphone addiction on academic performance. Computers & Education. 2016; 98:81–89.
8. Basel A, McAlaney J, Skinner T, Pleva M, Ali R. Defining digital addiction: Key features from the literature. Psihologija. 2020; 53(3):237–253.
9. Lin Y, Chang L, Lee Y, Tseng H, Kuo T, Chen S. Development and Validation of the Smartphone Addiction Inventory (SPAI). PLoS ONE. 2014; 9(6):e98312. https://doi.org/10.1371/journal.pone.0098312 PMID: 24896252
10. Lin Y, Chiang C, Lin P, Chang L, Ko C, Lee Y, et al. Proposed Diagnostic Criteria for Smartphone Addiction. PLOS ONE. 2016; 11(11):e0163010. https://doi.org/10.1371/journal.pone.0163010 PMID: 27846211
11. Hawi N, Samaha M, Griffiths M. The Digital Addiction Scale for Children: Development and Validation. Cyberpsychology, Behavior, and Social Networking. 2019; 22(12):771–778. https://doi.org/10.1089/cyber.2019.0132 PMID: 31755742
12. Abendroth A, Parry D, le Roux D, Gundlach J. An analysis of problematic media use and technology use addiction scales–what are they actually assessing? Responsible Design, Implementation and Use of Information and Communication Technology. 2020.
13. Grant J, Potenza M, Weinstein A, Gorelick D. Introduction to Behavioral Addictions. The American Journal of Drug and Alcohol Abuse. 2010; 36(5):233–241. https://doi.org/10.3109/00952990.2010.491884 PMID: 20560821
14. Madden GJ, Johnson PS. A delay-discounting primer. Impulsivity: The behavioral and neurological science of discounting. 2010:11–37.
15. Odum AL. Delay discounting: I'm a k, you're a k. Journal of the Experimental Analysis of Behavior. 2011 Nov; 96(3):427–39. https://doi.org/10.1901/jeab.2011.96-423 PMID: 22084499
16. Odum AL. Delay discounting: Trait variable?. Behavioural Processes. 2011; 87(1):1–9. https://doi.org/10.1016/j.beproc.2011.02.007 PMID: 21385637
17. Kirby KN, Petry NM, Bickel WK. Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. Journal of Experimental Psychology: General. 1999; 128(1):78–87. https://doi.org/10.1037//0096-3445.128.1.78 PMID: 10100392.
18. Bickel W, Odum A, Madden G. Impulsivity and cigarette smoking: delay discounting in current, never, and ex-smokers. Psychopharmacology. 1999; 146(4):447–454. https://doi.org/10.1007/pl00005490 PMID: 10550495

19. Alessi S, Petry N. Pathological gambling severity is associated with impulsivity in a delay discounting procedure. Behavioural Processes. 2003; 64(3):345–354. https://doi.org/10.1016/s0376-6357(03)00150-5 PMID: 14580703

20. Dixon MR, Marley J, Jacobs EA. Delay discounting by pathological gamblers. Journal of Applied Behavior Analysis. 2003; 36(4):449–58. https://doi.org/10.1901/jaba.2003.36-449 PMID: 14768665

21. Epstein LH, Salvy SJ, Carr KA, Dearing KK, Bickel WK. Food reinforcement, delay discounting and obesity. Physiology & Behavior. 2010; 100(5):438–45. https://doi.org/10.1016/j.physbeh.2010.04.029 PMID: 20435052

22. Peters J, Büchel C. The neural mechanisms of inter-temporal decision-making: understanding variability. Trends in Cognitive Sciences. 2011 May; 15(5):227–39. https://doi.org/10.1016/j.tics.2011.03.002 PMID: 21497544.

23. Tian M, Tao R, Zheng Y, Zhang H, Yang G, Li Q, et al. Internet gaming disorder in adolescents is linked to delay discounting but not probability discounting. Computers in Human Behavior. 2018; 80:59–66.

24. Schulz van Endert T, Mohr P. Likes and impulsivity: Investigating the relationship between actual smartphone use and delay discounting. PLOS ONE. 2020; 15(11):e0241383. https://doi.org/10.1371/journal.pone.0241383 PMID: 33206673

25. Hammond C, Mayes L, Potenza M. Neurobiology of Adolescent Substance Use and Addictive Behaviors: Prevention and Treatment Implications. Adolescent Medicine State of the Art Reviews. 2014; 25(1):15–32. PMID: 25022184

26. Baler R, Volkow N. Drug addiction: the neurobiology of disrupted self-control. Trends in Molecular Medicine. 2006; 12(12):559–566. https://doi.org/10.1016/j.molmed.2006.10.005 PMID: 17070107

27. Geier C, Luna B. The maturation of incentive processing and cognitive control. Pharmacology Biochemistry and Behavior. 2009; 93(3):212–221. https://doi.org/10.1016/j.pbb.2009.01.021 PMID: 19593842

28. Tang Y, Posner M, Rothbart M, Volkow N. Circuitry of self-control and its role in reducing addiction. Trends in Cognitive Sciences. 2015; 19(8):439–444. https://doi.org/10.1016/j.tics.2015.06.007 PMID: 26235449

29. McClure S. Separate Neural Systems Value Immediate and Delayed Monetary Rewards. Science. 2004; 306(5695):503–507. https://doi.org/10.1126/science.1100907 PMID: 15486304

30. Aertgeerts B, Buntinx F. The relation between alcohol abuse or dependence and academic performance in first-year college students. Journal of Adolescent Health. 2002; 31(3):223–225. https://doi.org/10.1016/s1054-139x(02)00362-2 PMID: 12225733

31. Samaha M, Hawi N. Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. Computers in Human Behavior. 2016; 57:321–325.

32. Akhter N. Relationship between Internet Addiction and Academic Performance among University Undergraduates. Educational Research and Reviews. 2013; 8(19):1793–1796.

33. Griffiths M. A 'components' model of addiction within a biopsychosocial framework. Journal of Substance Use. 2005; 10(4):191–197.

34. Behavioral impulsivity and risk-taking trajectories across early adolescence in youths with and without family histories of alcohol and other drug use disorders.

35. Dougherty D, Lake S, Mathias C, Ryan S, Bray B, Charles N, et al. Behavioral Impulsivity and Risk-Taking Trajectories Across Early Adolescence in Youths With and Without Family Histories of Alcohol and Other Drug Use Disorders. Alcoholism: Clinical and Experimental Research. 2015; 39(8):1501–1509.

36. Best J, Theim K, Gredysa D, Stein R, Welch R, Saelens B, et al. Behavioral economic predictors of overweight children's weight loss. Journal of Consulting and Clinical Psychology. 2012; 80(6):1086–1096. https://doi.org/10.1037/a0029827 PMID: 22924332

37. Epstein LH, Richards JB, Saad FG, Paluch RA, Roemmich JN, Lerman C. Comparison between two measures of delay discounting in smokers. Experimental and Clinical Psychopharmacology. 2003; 11(2):131–8. https://doi.org/10.1037/1064-1297.11.2.131 PMID: 12755457.

38. Lagorio CH, Madden GJ. Delay discounting of real and hypothetical rewards III: Steady-state assessments, forced-choice trials, and all real rewards. Behavioural Processes. 2005 May 31; 69(2):173–87. https://doi.org/10.1016/j.beproc.2005.02.003 PMID: 15845306

39. Myerson J, Baumann AA, Green L. Discounting of delayed rewards: (A)theoretical interpretation of the Kirby questionnaire. Behavioural Processes. 2014 Sep; 107:99–105. https://doi.org/10.1016/j.beproc.2014.07.021 PMID: 25139835.

40. Kaplan BA, Lemley SM, Reed DD, Jarmolowicz DP. 21- and 27-Item Monetary Choice Questionnaire Automated Scorer [software]. 2014. http://hdl.handle.net/1808/15424.

41. Kaplan BA, Amlung M, Reed DD, Jarmolowicz DP, Mckerchar TL, Lemley SM. Automating Scoring of Delay Discounting for the 21- and 27-Item Monetary Choice Questionnaires. The Behavior Analyst. 2016 Aug 19; 39(2):293–304. https://doi.org/10.1007/s40614-016-0070-9 PMID: 31976983.

42. Bertrams A, Dickhäuser O. Messung dispositioneller selbstkontroll-kapazität: eine deutsche adaptation der kurzform der self-control scale (SCS-KD). Diagnostica. 2009 Jan; 55(1):2–10.

43. Tangney JP, Baumeister RF, Boone AL. High Self-Control Predicts Good Adjustment, Less Pathology, Better Grades, and Interpersonal Success. Journal of Personality. 2004; 72(2):271–324. https://doi.org/10.1111/j.0022-3506.2004.00263.x PMID: 15016066.

44. Duckworth A, Tsukayama E, May H. Establishing Causality Using Longitudinal Hierarchical Linear Modeling: An Illustration Predicting Achievement From Self-Control. Social Psychological and Personality Science. 2010; 1(4):311–317. https://doi.org/10.1177/1948550609359707 PMID: 20976121

45. Wilmer HH, Chein JM. Mobile technology habits: patterns of association among device usage, intertemporal preference, impulse control, and reward sensitivity. Psychonomic Bulletin & Review. 2016 Mar 15; 23(5):1607–14.

46. Maxwell SE, Cole DA, Mitchell MA. Bias in Cross-Sectional Analyses of Longitudinal Mediation: Partial and Complete Mediation Under an Autoregressive Model. Multivariate Behavioral Research. 2011; 46 (5):816–41. https://doi.org/10.1080/00273171.2011.606716 PMID: 26736047

47. Yeun Y, Han S. Effects of Psychosocial Interventions for School-aged Children's Internet Addiction, Self-control and Self-esteem: Meta-Analysis. Healthcare Informatics Research. 2016; 22(3):217. https://doi.org/10.4258/hir.2016.22.3.217 PMID: 27525163

48. Amez S, Baert S. Smartphone use and academic performance: A literature review. International Journal of Educational Research. 2020; 103:101618.

49. Parry D, Davidson BI, Sewall C, Fisher JT, Mieczkowski H, Quintana DS. A Systematic Review and Meta-Analysis of Discrepancies Between Logged and Self- Reported Digital Media Use. PsyArXiv [Preprint]. 2020 [cited 2020 Feb 10]. Available from: https://doi.org/10.31234/osf.io/f6xvz.

50. Flake JK, Pek J, Hehman E. Construct Validation in Social and Personality Research. Social Psychological and Personality Science. 2017; 8(4):370–8.

51. Laconi S, Rodgers RF, Chabrol H. The measurement of Internet addiction: A critical review of existing scales and their psychometric properties. Computers in Human Behavior. 2014; 41:190–202.

52. Matta AD, Gonçalves FL, Bizarro L. Delay discounting: Concepts and measures. Psychology & Neuroscience. 2012 Dec 28; 5(2):135–46.

53. O'Donoghue T, Rabin M. Present bias: Lessons learned and to be learned. American Economic Review. 2015 May; 105(5):273–79.

54. Koffarnus M, Bickel W. A 5-trial adjusting delay discounting task: Accurate discount rates in less than one minute. Experimental and Clinical Psychopharmacology. 2014; 22(3):222–228. https://doi.org/10.1037/a0035973 PMID: 24708144

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Delay Discounting of Monetary and Social Media Rewards: Magnitude and Trait Effects

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Humans discount rewards as a function of the delay to their receipt. This tendency is referred to as delay discounting and has been extensively researched in the last decades. The magnitude effect (i.e., smaller rewards are discounted more steeply than larger rewards) and the trait effect (i.e., delay discounting of one reward type is predictive of delay discounting of other reward types) are two phenomena which have been consistently observed for a variety of reward types. Here, we wanted to investigate if these effects also occur in the context of the novel but widespread reward types of Instagram followers and likes and if delay discounting of these outcomes is related to self-control and Instagram screen time. In a within-subject online experiment, 214 Instagram users chose between smaller, immediate and larger, delayed amounts of hypothetical money, Instagram followers and likes. First, we found that the magnitude effect also applies to Instagram followers and likes. Second, delay discounting of all three reward types was correlated, providing further evidence for a trait influence of delay discounting. Third, no relationships were found between delay discounting and self-control as well as Instagram screen time, respectively. However, a user's average like count was related to delay discounting of Instagram likes.

Keywords: delay discounting, impulsivity, social media, Instagram, magnitude effect, intertemporal choice, trait effect

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INTRODUCTION

Many decisions in life imply a trade-off between the size of rewards and the delay toward attaining them. When dieting, for example, people forgo a smaller, immediate reward (enjoying an unhealthy snack) in favor of a greater benefit (improved health outcomes) in the future. Similarly, saving money implies preferring to wait for a compounded amount instead of spending a smaller amount in the present. These intertemporal trade-offs have been studied thoroughly in the last decades among human and non-human animals (Ainslie, 1975; Green et al., 1981; Mischel et al., 1989; Kirby and Maraković, 1995; Perry et al., 2005). Both have been found to discount rewards as a function of the delay to receiving them; this process is referred to as delay discounting (Mazur, 1987).

In a typical delay discounting experiment, participants are faced with repeated choices between a smaller, immediately available monetary amount (e.g., USD50 today) and a larger, delayed reward (e.g., USD100 in 7 days). The reward amounts and delays are systematically varied and based on the participant's choices an individual discount rate can be calculated. Various models that seek to explain discounting behavior have emerged, with the hyperbolic decay model (Mazur, 1987) being able to provide the best fit for most empirical data. According to this model, behavior can be mathematically described by the equation $V = A/(1 + kD)$, where V is the present value of the future reward, A is the reward amount and D is the delay associated with the reward. The free parameter k represents an individual's discount rate and is often used as a measure of behavioral impulsivity. The larger the discount rate, the more a future reward is devalued, which characterizes a relatively more impulsive individual.

Several phenomena have been observed in the delay discounting literature, of which two are further investigated in this study. One of the early findings was the magnitude effect (Thaler, 1981; Green et al., 1994; Kirby and Maraković, 1995), which describes the human tendency to discount smaller rewards more steeply than larger rewards, i.e., people behave more impulsively when having to choose between, e.g., USD10 now vs. USD50 in 1 year compared to a setting with, e.g., USD1,000 now vs. USD5,000 in 1 year. This pattern of behavior is at odds with classical economic theory, which posits that intertemporal choices should be consistent if the annual interest rate is the same (Loewenstein and Thaler, 1989). Shefrin and Thaler (1988) initially proposed mental accounting as an explanation for the magnitude effect, according to which small amounts of money are placed into a mental checking account, mainly dedicated to consumption, and large amounts of money are entered into a mental savings account. Waiting for a small amount thus implies forgoing consumption, whereas waiting for a large amount means forgoing interest earnings. If consumption is perceived as more attractive than interest, decision-makers will choose more impulsively for small rewards and less impulsively for large rewards. However, this explanation is made less plausible by the finding that the magnitude effect also occurs with non-monetary rewards [e.g., health (Chapman and Elstein, 1995)], for which the checkings/savings logic is not meaningful. As a more generic alternative, Loewenstein and Prelec (1992) attributed the magnitude effect to the shape of decision-makers' value function, which is sharply convex for small outcomes but becomes more elastic for large outcomes. According to this account, individuals do not perceive much difference in value between two small outcomes (e.g., 5 units now and 10 units in 6 months), causing them to choose the immediately available option. However, despite having the same ratio, individuals perceive a larger value difference between, e.g., 50 units now and 100 units in 6 months, resulting in choice for the larger, delayed outcome. Thus, decision-makers are sensitive not only to relative but also absolute differences in reward amounts (Prelec and Loewenstein, 1991).

Another phenomenon commonly observed is a trait-like influence on delay discounting, which is demonstrated by the reliability of delay discounting behavior across time, test instruments, context and reward types (Odum et al., 2020). People's discount rates have been shown to be stable when retested weeks (Beck and Triplett, 2009) or even years (Anokhin et al., 2015) after the initial assessment. Additionally, delay discounting elicited with one type of test is strongly correlated with results obtained with other types of tests (Smith and Hantula, 2008). Lastly, an individual's discounting behavior in one context or for one type of reward has been found to be predictive of delay discounting in another context and for another reward (Dixon et al., 2003; Johnson et al., 2010; Odum, 2011). For example, an individual behaving impulsively toward food tends to discount entertainment relatively steeply as well (Charlton and Fantino, 2008). While a slight shift in preferences is observed in these studies (suggesting a state influence), an individual's discount rates remain similar (reflecting a trait influence). The trait perspective on delay discounting is supported by recent evidence of a genetic basis of delay discounting; studies in humans (Anokhin et al., 2011) and rodents (Wilhelm and Mitchell, 2009) have shown that genetic differences can account for a significant portion of inter-individual differences in delay discounting behavior.

The magnitude and the trait effect have been shown for various types of rewards, such as money (Green et al., 1997), food and drinks (Odum et al., 2006; Jimura et al., 2009), entertainment (Friedel et al., 2014), and even abused substances (Giordano et al., 2002). However, the question if these findings extend to the relatively new phenomenon of social media rewards has yet to be addressed. Social media, such as Facebook or Instagram, have become immensely popular since the 2000s and currently have 2.9 billion (Facebook) and 1 billion (Instagram) monthly active users (Facebook Inc, 2021a,b). Instagram is especially prevalent among the segment of 18- to 34-year olds, making up more than 60% of its user base (Statista, 2021). On the platform, users publish pictures and videos, which are saved to the users' profile page. Other users may choose to like these posts and follow other users' accounts in order to receive updates about their activities. The number of followers and likes associated with an account have become highly demanded metrics, which even lead to the formation of businesses that sell fake, computer-generated followers and likes in order to artificially boost an account's popularity. Some popular media have even referred to these metrics as "social currency" (Colcol, 2020). Our main goal in this present study is to investigate if the past findings on the magnitude effect as well as the trait effect of delay discounting can be extended toward the novel rewards of Instagram followers and likes. Thus, the first two hypotheses for this present study are as follows:

H1: Delay discounting of Instagram followers and likes decreases as reward size increases.

H2: Delay discounting of money, Instagram followers and likes are correlated.

To gain a deeper understanding of its underlying processes, delay discounting has been a frequent topic of neuroscientific studies. While the debate about the exact neural regions involved in delay discounting is still ongoing, researchers have found common ground on the central role that self-control processes play in the context of delay discounting (Peters and Büchel, 2011). According to prominent accounts, individuals with greater ability to control thoughts, emotions and behavior can better withstand the temptation of the immediate reward and thus tend to make the less impulsive choice for the larger, delayed reward (McClure et al., 2004; Berns et al., 2007). A recent meta-analysis has indeed shown that self-control is a reliable predictor of delay discounting behavior (Duckworth and Kern, 2011). In this present study, we seek to replicate these findings in the context of social media rewards.

Lastly, recent studies have found an association between screen time, i.e., time spent with a smartphone, laptop or tablet, and delay discounting (Wilmer and Chein, 2016; Schulz van Endert and Mohr, 2020). While the direction of causality is unknown, people who spend more time with digital devices tend to choose more impulsively in delay discounting tasks with monetary rewards. Here, we want to investigate if this relationship also exists when people choose between immediate and delayed Instagram followers and likes. Therefore, our hypotheses 3 and 4 are as follows:

H3: Self-control is negatively correlated with delay discounting of money, Instagram followers and likes.

H4: Screen time is positively correlated with delay discounting of money, Instagram followers and likes.

Our empirical investigation extends previous findings on the magnitude and trait effect of delay discounting, while it also yielded unexpected null findings concerning the relationships with self-control and screen time. We discuss the implications and limitations of this present study and offer possible directions of future research.

MATERIALS AND METHODS

Participants

In total, 218 adult participants (median age 25 years, 55% female) were recruited from the online participant pool Prolific. The sample size was determined to exceed that of related laboratory studies (typically less than 100 participants) while accounting for possibly reduced data quality of an online experiment. After initial screening four participants were excluded from further analyses due to consistency scores below the recommended threshold of 75% (see below), resulting in a final sample size of 214. There were two requirements for participation: first, participants needed to be fluent in English as the experiment used original versions of various scales (see section "Measures"). Second, participants needed to be regular Instagram users, which was defined as using the app at least once per week. Compensation was based on an hourly rate of USD10.50 recommended by Prolific. All participants were informed about the purpose and contents of the study in written form and agreed to the study conditions upon participation.

Measures

Delay Discounting

Participants' discounting of future rewards was assessed with the 27-item Monetary Choice Questionnaire (MCQ; Kirby et al., 1999). In this questionnaire participants repeatedly choose either a smaller, immediately available or a larger amount of money available in the future. The instrument comprises three groups of nine items based on the magnitude of the larger, delayed reward. The grouping is as follows: small (USD25, USD30, and USD35), medium (USD50, USD55, and USD60) and large (USD75, USD80, and USD85) magnitudes. The smaller, immediate rewards range from USD11 to USD80. The range of delays to the rewards is seven to 186 days, all outcomes being hypothetical in this study. Based on the participant's choices, an individual discount rate can be calculated under the assumption of hyperbolic discounting. As a simple and atheoretical alternative, the proportion of choices of the larger delayed reward (LDR) can be used as a measure of delay discounting (Myerson et al., 2014), i.e., the lower the proportion, the more the individual devalues future rewards. The MCQ has been used extensively in the literature as its results are comparable to more comprehensive scales (Epstein et al., 2003) as well as to paradigms that use real or potentially real rewards (Lagorio and Madden, 2005). The current data showed high correlations between the LDR proportions and the natural log of the discount parameter k according to Mazur (1987) (all r's < -0.95, all p's < 0.001) for all outcomes, indicating that the LDR measure was accurately assessing participants' discounting of future rewards.

To assess participants' delay discounting in an Instagram context, the rewards of the MCQ were simply changed to followers and likes, respectively, while the delays and amounts remained identical. Conveniently, these parameters resemble what a personal Instagram user realistically encounters (fewer than 100 likes, waiting periods of less than 6 months). Additionally, having the same delay ranges and the same number of units of rewards enabled us to use the scoring methodology of the MCQ for both Instagram rewards. To simulate an Instagram setting, in addition to written text, the official Instagram icons showing the respective amounts of followers and likes were used with the corresponding delays displayed below the icons (see **Figure 1**). To clarify that the offered amounts of followers and likes represented incremental increases rather than the existing balances of followers and likes of participants' Instagram accounts, the formulations "additional followers " and "additional likes" were used in the choice trials. The responses to the MCQ for all outcomes were scored with Kaplan et al.'s (2014) automated scoring tool. The tool provides the overall LDR proportion (based on all 27 trials) as well as proportions for small, medium and large rewards. In order to identify participants showing insufficient comprehension or lack of effort, the tool also provides consistency scores. Four participants had consistency scores below the recommended threshold of 75% (Kaplan et al., 2016), resulting in their exclusion from the analyses.

Self-Control

To measure participants' trait self-control we used Tangney et al.'s (2004) Brief Self-Control Scale. This widely used scale requires participants to report to what extent they agree with statements such as "I have a hard time breaking bad habits" or "People would say I have iron self-discipline." The brief 13-item version was employed as it has been shown to be equally reliable and valid as the 36-item version (Tangney et al., 2004). Scores range from 13 to 65, higher scores indicating better ability to control thoughts, emotions and behavior. Good internal consistency was indicated by Cronbach's α of 0.85.

Instagram Preferences

As there may be differences in participants' goals and attitudes toward Instagram rewards, we included six statements that coarsely elicited participants' (1) future preference for followers

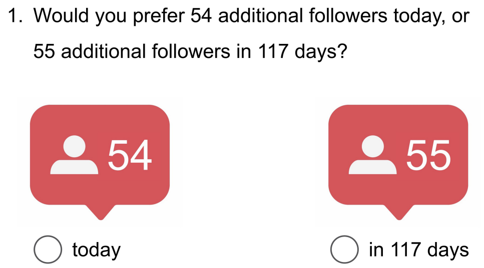

FIGURE 1 | Exemplary choice trial from the delay discounting task for followers.

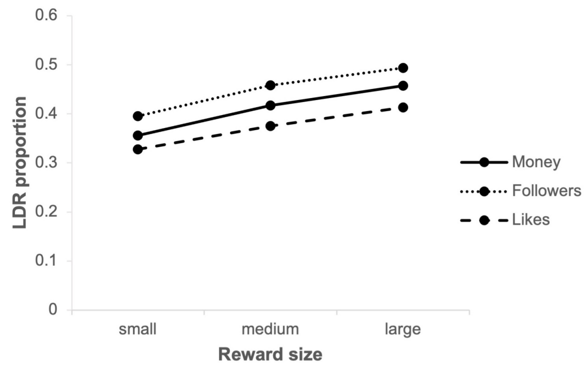

FIGURE 2 | Mean LDR proportions by reward size.

and likes (i.e., how attractive getting followers and likes will be for them personally in the near future) (2) view on the objective future worth of followers and likes (i.e., if they project the worth of followers and likes in the general population to increase or decrease), and (3) motivation to maximize followers and likes (i.e., how important it is for them personally to get as many followers and likes as possible). These statements are based on hypotheses proposed by Odum et al. (2020), which may help explain individual differences in delay discounting behavior. The items were scored on a five-point Likert scale, higher scores representing higher future preference, higher objective future worth and higher motivation, respectively.

Additional Variables

Participants also had to estimate their average daily usage duration of Instagram. Next, they stated what year they had joined the platform and whether their profile was private (posts only visible to approved followers) or public (posts visible to anyone). Furthermore, they were asked to indicate the number of followers they had and the average number of likes they typically got on one of their posts. For exploratory purposes, the personality trait of Extraversion was elicited using the 10 Item Personality Measure (Gosling et al., 2003). Lastly, age, gender, education, and discretionary income were elicited as control variables.

Procedure

All participants underwent the three main experimental conditions of delay discounting of money, Instagram followers and Instagram likes. To control for order effects, Latin Square counterbalancing was employed among these three conditions, i.e., each version of the delay discounting measure occurred only once in any order position. Other measures remained in the same position, resulting in the following order of tasks: (1) MCQ for first outcome (2) Brief Self-Control Scale (3) MCQ for second outcome (4) Ten Item Personality Measure (5) MCQ for third outcome, (6) control variables, and (7) Instagram preferences. The study was conducted in three sessions throughout July 2021 with roughly 70 participants each, one session lasting about 20 min, on average. The study was approved by the German Association for Experimental Economic Research (approval no. x61nvgzI).

Statistical Analysis

Initially, the distributions of the delay discounting measures were analyzed for normality by means of Shapiro-Wilk tests. Non-parametric analyses were subsequently used for these variables. To investigate differences in delay discounting between different reward sizes (related to hypothesis H1), the Friedman test, as a non-parametric alternative to the repeated-measures ANOVA, was used. As a follow-up analysis, the difference between delay discounting measures for two different reward sizes (e.g., small money vs. medium money) was analyzed with Wilcoxon signed-rank tests. All associations in this study (related to hypotheses H2, H3, and H4 and variables on an ordinal scale) were analyzed by means of Spearman rank correlations with prior log-transformation of highly skewed variables. The difference between correlation coefficients of delay discounting measures for the three reward types was tested with asymptotic z-tests. Lastly, for multivariate analyses (related to hypotheses H3 and H4) multiple linear regression was employed.

RESULTS

Magnitude Effect of Delay Discounting

Hypothesis H1 states that delay discounting decreases as reward magnitude increases. **Figure 2** shows the mean LDR proportions by reward size for the three different outcomes in this study. The distributions of all proportions appeared approximately normal with a slightly disproportionate number of participants at both extremes; Shapiro-Wilk tests rejected normality (all p-values < 0.001). For all outcomes, Friedman tests showed that delay discounting of small, medium and large rewards were statistically different (Money: $\chi^2(2) = 142.985$, $p < 0.001$; Followers: $\chi^2(2) = 102.318$, $p < 0.001$; Likes: $\chi^2(2) = 95.648$, $p < 0.001$). Follow-up Wilcoxon signed-rank tests confirmed that the LDR proportions of medium rewards were higher than of small rewards for all outcomes (all p-values < 0.001) and that the LDR proportions of large rewards were higher than of medium rewards for all outcomes (all p-values < 0.001), confirming our first hypothesis.

In an attempt to shed light on possible reasons for individual discounting patterns, we investigated the associations between the participants' stated Instagram preferences with regard to followers and likes and their overall delay discounting of followers and likes (across all reward sizes), respectively. We found the strongest relationship between an individual's future preference for followers and their overall delay discounting of followers but this relationship was not statistically significant ($\rho = -0.11$, $p = 0.126$). Furthermore, neither participants' view on the future worth of followers ($\rho = -0.09$, $p = 0.194$) nor their motivation to maximize followers ($\rho = -0.04$, $p = 0.556$) were significantly related to the overall LDR proportion for followers. Looking at the participants' corresponding attitudes toward likes, neither their future preference for likes ($\rho = -0.01$, $p = 0.842$) nor their view on the future worth of likes ($\rho = 0.00$, $p = 0.990$) nor their motivation to maximize likes ($\rho = -0.04$, $p = 0.556$) were correlated with overall delay discounting of likes.

Trait Influence of Delay Discounting

Due to the trait-like character of delay discounting, hypothesis H2 states that the LDR proportions for the three outcomes money, followers and likes are correlated. **Table 1** shows bivariate Spearman correlations between the main variables in this study. All three LDR measures were significantly intercorrelated, confirming hypothesis 3. The LDR proportions for followers and LDR proportions for likes had the strongest relationship ($\rho = 0.60$, $p < 0.001$). The correlation between LDR money and LDR likes was $\rho = 0.45$ with $p < 0.001$, while LDR money and LDR followers showed the weakest association ($\rho = 0.35$, $p < 0.001$). All three correlation coefficients were significantly different from one another (all p-values < 0.05). To further investigate the relationships between delay discounting of these three rewards, we also calculated correlations between the sub-measures (LDR proportions for small, medium and large rewards). As shown in **Table 2**, within reward types the correlations were all high (all ρ's > 0.70, all p's < 0.001). Comparing followers with money, small amounts of followers were discounted most similarly as small amounts of money ($\rho = 0.41$, $p < 0.001$), whereas the weakest correlation was found between the LDR for small amounts of followers and the LDR for large amounts of money ($\rho = 0.24$, $p < 0.001$). Comparing followers with likes, medium amounts of followers were discounted most similarly as medium amounts of likes ($\rho = 0.59$, $p < 0.001$), whereas the weakest correlation was found between the LDR for small amounts of followers and the LDR for large amounts of likes ($\rho = 0.46$, $p < 0.001$). Comparing money with likes, medium amounts of money were discounted most similarly as medium amounts of likes ($\rho = 0.48$, $p < 0.001$), whereas the weakest correlation was found between the LDR for small amounts of money and the LDR for large amounts of likes ($\rho = 0.30$, $p < 0.001$).

Correlates of Delay Discounting

Hypotheses H3 and H4 state that self-control is negatively correlated and that screen time is positively correlated with delay discounting of money, followers and likes. Therefore, the associations of both self-control and Instagram screen time with the three measures of delay discounting, respectively, were analyzed. As shown in **Table 1**, neither self-control nor Instagram screen time were correlated with any of the three LDR proportions. Notably, self-control was not correlated with any of the main variables in this study. Screen time was positively related to participants' amount of existing followers ($\rho = 0.22$, $p < 0.01$) and to the average number of likes participants receive for a post ($\rho = 0.29$, $p < 0.001$). To analyze associations between the main variables simultaneously, we performed three multiple regression analyses with the LDR proportions for the three reward types as dependent variables and self-control, extraversion and demographic as well as Instagram-related measures as independent variables. All assumptions for multiple linear regression were met. The results of these analyses confirmed that neither self-control nor Instagram screen time could predict delay discounting of money, followers or likes. However, the average number of likes a person typically receives for an Instagram post significantly predicted the LDR proportion of likes ($\beta = -0.26$, $p = 0.016$) when accounting for psychological and demographic variables, as displayed in **Table 3**. The overall model yielded an R^2 of 0.05, F-statistic of 0.77 and p-value of 0.70.

DISCUSSION

The primary goal of this study was to investigate if two well-known phenomena of delay discounting, namely the magnitude effect and the trait effect, also occur in the context of the novel reward types of Instagram followers and likes. Looking initially at the effect of varying reward magnitudes, the present data showed that small rewards were discounted more steeply than medium rewards and that medium rewards were discounted more steeply than large rewards. This magnitude effect occurred for all three outcomes in this study, i.e., money, Instagram followers and likes, which confirmed hypothesis H1. Thus, with the MCQ modified for Instagram rewards, we were able to replicate past findings on the magnitude effect with monetary (e.g., Thaler, 1981; Green et al., 1994; Kirby and Maraković, 1995) and non-monetary (e.g., Baker et al., 2003; Estle et al., 2007; Lawyer et al., 2010) rewards. A prevalent account holds that the magnitude effect is due to the shape of the decision-maker's value function being convex for small gains and straightening out for large gains (Loewenstein and Prelec, 1992). This property implies that when comparing two equivalent ratios (e.g., USD5/USD1 and USD500/USD100), the ratio involving larger gains is perceived as larger, resulting in less impulsive choices. The present results suggest that Instagram followers and likes, being new, non-consumable rewards from the digital sphere, are subject to a value function with a similar curvature as other well-researched outcomes, such as money, food and drinks, entertainment or addictive substances. In an Instagram user context the magnitude effect implies that people seem to be more impulsive when the number of additional followers and likes they receive is relatively lower, such as when they have posted less popular content. In contrast, when a photograph or video post is being received more positively users seem to be more willing to wait for any additional followers and likes. An interesting question for future research

TABLE 1 | Correlations between main variables.

Variable	1	2	3	4	5	6	7	8	9	10	11
1. LDR followers	–										
2. LDR money	0.35***	–									
3. LDR likes	0.60***	0.45***	–								
4. Self-control	0.05	0.05	0.05	–							
5. Extraversion	−0.04	0.01	−0.02	0.06	–						
6. Income[a]	−0.13	0.08	−0.06	−0.05	−0.07	–					
7. Instagram screen time[a]	−0.01	−0.02	−0.04	−0.01	−0.02	−0.15*	–				
8. Existing followers[a]	−0.02	−0.01	0.04	0.11	0.22**	−0.01	0.22**	–			
9. Average likes[a]	0.01	−0.00	−0.06	0.11	0.22**	−0.12	0.29***	0.68***	–		
10. Active years	0.05	−0.07	0.05	−0.09	0.11	0.08	0.09	0.31***	0.25***	–	
11. Age[a]	−0.18**	0.09	0.01	−0.07	−0.01	0.30***	−0.14*	−0.22**	−0.45***	0.03	–

**p* < 0.05, ***p* < 0.01, and ****p* < 0.001.
[a]*Log transformed.*
Spearman correlations.

TABLE 2 | Correlations between delay discounting sub-measures.

Variable	1	2	3	4	5	6	7	8	9
1. LDR followers large	–								
2. LDR followers medium	0.86***	–							
3. LDR followers small	0.76***	0.81***	–						
4. LDR money large	0.26***	0.27***	0.24***	–					
5. LDR money medium	0.30***	0.35***	0.35***	0.79***	–				
6. LDR money small	0.27***	0.31***	0.41***	0.73***	0.80***	–			
7. LDR likes large	0.52***	0.53***	0.46***	0.35***	0.41***	0.30***	–		
8. LDR likes medium	0.58***	0.59***	0.53***	0.42***	0.48***	0.39***	0.84***	–	
9. LDR likes small	0.50***	0.53***	0.49***	0.37***	0.44***	0.39***	0.77***	0.80***	–

****p < 0.001.*
Spearman correlations.

could be if this shift in impulsivity spills over onto behavior outside the platform, i.e., do people choose more impulsively (e.g., at work, while shopping) when they have posted content on social media which is receiving relatively less appreciation? Such an effect, if observed, would then have to be disentangled from any mood changes induced by relatively less positive social feedback (see e.g., Burrow and Rainone, 2017).

We also analyzed the trait effect of delay discounting, which manifests itself in the association of delay discounting of one outcome with that of other outcomes. The present data provide strong support for a trait influence, as delay discounting of money, followers and likes were all correlated, thus confirming hypothesis H2. This cross-outcome reliability has been shown in many previous studies (Odum et al., 2020) and indicates that state-dependent shifts of delay discounting (caused by e.g., different contexts or rewards) occur at different baselines, which represent the trait influence. Thus, a highly impulsive person with regard to money might behave slightly differently in an Instagram context but will nonetheless be characterized by rather impulsive choices. The correlation between delay discounting of followers and likes was the strongest, which is an intuitive result given that both types of rewards are social in nature and stem from the same platform. Surprisingly, money discounting and follower discounting had the weakest association in this study. The number of Instagram followers associated with an account is a rather stable metric which may be considered an account balance, thus sharing some characteristics with money. The number of likes a user receives, on the other hand, matters most immediately after content was posted since this signals the Instagram algorithm that the post is attractive, resulting in content to be displayed more prominently. Additional followers are typically received much less frequently than additional likes, whose magnitudes also fluctuate considerably more. Thus, it is somewhat puzzling that, vis-a-vis delay discounting of followers, delay discounting of likes had more shared variance with delay discounting of money. Breaking down delay discounting by reward magnitude showed that inter-correlations were not the highest for matched reward sizes (e.g., small money vs. small followers, medium likes vs. medium followers). This may be an indication that the three rewards were not of equal subjective value to participants. Indeed, reward magnitudes in the three delay discounting tasks were not scaled to equivalent (monetary or subjective) value in this study, precluding a direct comparison of discount rates. Any differences in discount rates may simply be due to different value functions of the three rewards rather than due to differences in reward characteristics *per se* (see Chapman (1996) for a detailed discussion). Our data seem to suggest that delay discounting for the three rewards was different [indicating

TABLE 3 | Multiple regression analysis of LDR likes.

Term	B	SE B	95% CI		β	*t*	*p*
			LL	UL			
Intercept	0.47	0.27	−0.07	1.00	0.00	1.72	0.087
Self-control	0.00	0.00	0.00	0.01	0.11	1.46	0.146
Extraversion	0.00	0.01	−0.02	0.02	−0.01	−0.17	0.863
Instagram screen time[a]	0.00	0.01	−0.03	0.03	−0.01	−0.12	0.904
Existing followers[a]	0.02	0.01	−0.01	0.05	0.16	1.61	0.110
Average likes[a]	−0.04	0.02	−0.07	−0.01	−0.26	−2.43	0.016
Profile (private)	−0.01	0.02	−0.04	0.02	−0.05	−0.70	0.487
Active years	0.01	0.01	−0.01	0.02	0.09	1.11	0.267
Age[a]	−0.04	0.07	−0.18	0.10	−0.05	−0.59	0.558
Gender (Female)	0.00	0.02	−0.03	0.03	0.02	0.27	0.786
Education (Bachelor)	0.02	0.03	−0.05	0.09	0.05	0.53	0.597
Education (High school)	−0.01	0.04	−0.08	0.06	−0.04	−0.39	0.695
Education (Master/Diploma)	0.03	0.04	−0.05	0.11	0.06	0.78	0.434
Education (Other)	−0.02	0.06	−0.14	0.10	−0.02	−0.33	0.745
Income[a]	−0.01	0.01	−0.04	0.01	−0.08	−1.12	0.265

[a]Log transformed.
Effect coding was applied for categorical variables.

a state effect (Odum et al., 2020)], but future research should investigate this hypothesis using calibrated reward magnitudes.

A surprising result was that self-control, typically a reliable predictor of delay discounting (Duckworth and Kern, 2011), was not related to delay discounting of money, followers and likes. Hence, our findings did not support hypothesis H3. Since the Brief Self-Control Scale is a self-report instrument, a possible explanation could be that participants did not answer as truthfully in this online study as they might have done in a lab-based setting. Similar reasoning may be applied to the null finding with regard to Instagram screen time. Here, we found that people's self-reported usage duration of the Instagram app was not associated with any of the three measures of delay discounting, which disproves hypothesis H4. Self-reported screen time has been shown to be an adequate indicator of actual screen time but app-based measures (e.g., Screen Time on iOS or Digital Wellbeing on Android, which have been used in related studies) are more accurate and should be used in combination with self-reports when available (Ohme et al., 2021). Additionally, in this present study we only elicited Instagram-related screen time instead of total screen time. Thus, screen time of gaming apps or other social media, which have previously been shown to be correlated with delay discounting (Schulz van Endert and Mohr, 2020), were not included. When accounting for psychological and demographic variables, we found that the average number of likes a person typically receives on one of their posts is predictive of delay discounting of likes. That is, the more likes a person is accustomed to, the more impulsive they are toward this kind of appreciation. The nature of the immediacy-oriented Instagram algorithm for likes described above may help explain this result. A person typically receiving plenty of likes is probably concerned about receiving likes quickly in order to maximize visibility on the platform's feed. In contrast, users with few likes usually received for their content seem to place less emphasis on increasing prominence and are thus more willing to wait for a higher number of likes, which are, due to the delay, less likely to boost this user's popularity. This interpretation is supported by the finding that individuals with higher average like count also reported a greater motivation to maximize followers and likes.

In an effort to understand the observed discounting patterns for Instagram rewards better, we also investigated these in relation to participants' attitudes and preferences. In spite of the majority of participants in this present study stating that their preference for Instagram likes will decrease in the near future, we did not find an association between people's future preference for likes and their delay discounting of likes. Participants' views on the objective future worth of likes turned out to be divided and did not provide any clues about delay discounting of likes either. Further, we found no association between participants' motivation to maximize likes and delay discounting of likes. When looking at the corresponding statements in terms of followers, we did not find any associations between participants' responses regarding the future preference, future worth or motivation to maximize and their delay discounting of followers. This certainly does not imply that these factors do not play a role in the context of Instagram rewards; rather, the puzzling results may simply be due to the elicitation method, which will be discussed below.

This study has several limitations, which may be addressed by future research. First, the same participants completed three similar delay discounting tasks in one session, which potentially introduced common method bias (Podsakoff et al., 2003). Future studies could create some temporal separation between the measurements or employ tasks with different (e.g., value-calibrated) reward magnitudes. Second, despite being an efficient instrument, the MCQ has some drawbacks. For instance, the smaller, sooner rewards are always available immediately (as opposed to choices where both rewards become available at different points in the future), bearing the risk of overweighting present bias (O'Donoghue and Rabin, 2015). Also, the identification of non-systematic responses is difficult for extreme discounting; always choosing the smaller, immediate reward as well as always choosing the larger, delayed reward are 100 percent consistent responses but may also stem from a lack of attending to the questionnaire. To address these points, future studies may employ computer-based, titrating delay discounting instruments, e.g., by Du et al. (2002), which adjust the reward amounts based on the participant's previous responses. Third, all rewards were hypothetical in this study. While this has been shown to be unproblematic for monetary rewards, we cannot rule out the possibility that participants would have behaved differently if they had actually received followers and likes for their Instagram account. Since purchasing and awarding followers and likes is commercially available, future studies could replicate our findings with real payoffs. Fourth participants' attitudes and goals toward Instagram were elicited in a brief and simple manner. To be able to shed more light on the reasons behind discounting of Instagram rewards, more elaborate tools to assess future preference, objective future worth and motivation to maximize rewards seem necessary. Fifth, our delay discounting measurement method did not allow for a direct comparison of discount rates for the three reward types. Non-monetary rewards are typically discounted less steeply than money [i.e., a state influence of delay discounting (Odum et al., 2020)] and the replication of this effect in the context of social media rewards lends itself as a topic for future research. Lastly, only participants who are regularly exposed to Instagram followers and likes, i.e., active users, were included in this study. Based on our data, we cannot make inferences about delay discounting of Instagram rewards by non-users or people unfamiliar with the platform. However, it is unlikely that the latter group would consider Instagram followers and likes as rewards, rendering an analysis meaningless. Instead, future studies could employ other kinds of social media rewards, such as Twitter followers and likes or Facebook likes, as these platforms tend to be used by different population groups.

Our study provided initial evidence that Instagram followers and likes, as novel yet widespread reward types, are processed in a similar way as previously studied rewards in the context of delay discounting. A person's general, trait-like impulsivity remains recognizable in the discounting patterns of Instagram rewards. Further research is needed to determine if these rewards also cause any temporary shifts in delay discounting on the one hand and to clarify the relationships between delay discounting of Instagram rewards and self-control as well as actual screen time on the other hand.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by the German Association for Experimental Economic Research. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

TS created the study concept, programmed the experiment, collected, and analyzed data, and wrote the manuscript. PM provided study funding, assistance during data analysis, and feedback for the manuscript. Both authors contributed to the article and approved the submitted version.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2022.822505/full#supplementary-material

REFERENCES

Ainslie, G. (1975). Specious reward: a behavioral theory of impulsiveness and impulse control. *Psychol. Bull.* 82, 463–496. doi: 10.1037/h0076860

Anokhin, A. P., Golosheykin, S., Grant, J. D., and Heath, A. C. (2011). Heritability of delay discounting in adolescence: a longitudinal twin study. *Behav. Genet.* 41, 175–183. doi: 10.1007/s10519-010-9384-7

Anokhin, A. P., Golosheykin, S., and Mulligan, R. C. (2015). Long-term test–retest reliability of delayed reward discounting in adolescents. *Behav. Processes* 111, 55–59. doi: 10.1016/j.beproc.2014.11.008

Baker, F., Johnson, M. W., and Bickel, W. K. (2003). Delay discounting in current and never-before cigarette smokers: similarities and differences across commodity, sign, and magnitude. *J. Abnorm. Psychol.* 112, 382–392. doi: 10.1037/0021-843x.112.3.382

Beck, R. C., and Triplett, M. F. (2009). Test–retest reliability of a group-administered paper–pencil measure of delay discounting. *Exp. Clin. Psychopharmacol.* 17, 345–355. doi: 10.1037/a0017078

Berns, G. S., Laibson, D., and Loewenstein, G. (2007). Intertemporal choice–toward an integrative framework. *Trends Cogn. Sci.* 11, 482–488. doi: 10.1016/j.tics.2007.08.011

Burrow, A. L., and Rainone, N. (2017). How many likes did I get?: purpose moderates links between positive social media feedback and self-esteem. *J. Exp. Soc. Psychol.* 69, 232–236.

Chapman, G. B. (1996). Temporal discounting and utility for health and money. *J. Exp. Psychol. Learn. Mem. Cogn.* 22, 771–791. doi: 10.1037//0278-7393.22.3.771

Chapman, G. B., and Elstein, A. S. (1995). Valuing the future: temporal discounting of health and money. *Med. Decis. Making* 15, 373–386. doi: 10.1177/0272989X9501500408

Charlton, S. R., and Fantino, E. (2008). Commodity specific rates of temporal discounting: does metabolic function underlie differences in rates of discounting? *Behav. Processes* 77, 334–342. doi: 10.1016/j.beproc.2007.08.002

Colcol, F. (2020). *Council Post: The Importance of Social Currency*. Available Online at: https://www.forbes.com/sites/theyec/2020/03/03/the-importance-of-social-currency/?sh=127781261678 [accessed November 24, 2021].

Dixon, M. R., Marley, J., and Jacobs, E. A. (2003). Delay discounting by pathological gamblers. *J. Appl. Behav. Anal.* 36, 449–458.

Du, W., Green, L., and Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *Psychol. Rec.* 52, 479–492.

Duckworth, A. L., and Kern, M. L. (2011). A meta-analysis of the convergent validity of self-control measures. *J. Res. Pers.* 45, 259–268. doi: 10.1016/j.jrp.2011.02.004

Epstein, L. H., Richards, J. B., Saad, F. G., Paluch, R. A., Roemmich, J. N., and Lerman, C. (2003). Comparison between two measures of delay discounting in smokers. *Exp. Clin. Psychopharmacol.* 11, 131–138. doi: 10.1037/1064-1297.11.2.131

Estle, S. J., Green, L., Myerson, J., and Holt, D. D. (2007). Discounting of monetary and directly consumable rewards. *Psychol. Sci.* 18, 58–63. doi: 10.1111/j.1467-9280.2007.01849.x

Facebook Inc (2021a). *FB Earnings Presentation Q2 2021*. Available Online at: https://s21.q4cdn.com/399680738/files/doc_financials/2021/q2/Q2-2021_Earnings-Presentation.pdf [accessed November 24, 2021].

Facebook Inc (2021b). *Instagram for Business*. Available Online at: https://www.facebook.com/business/marketing/instagram [accessed November 24, 2021].

Friedel, J. E., DeHart, W. B., Madden, G. J., and Odum, A. L. (2014). Impulsivity and cigarette smoking: discounting of monetary and consumable outcomes in current and non-smokers. *Psychopharmacology* 231, 4517–4526. doi: 10.1007/s00213-014-3597-z

Giordano, L. A., Bickel, W. K., Loewenstein, G., Jacobs, E. A., Marsch, L., and Badger, G. J. (2002). Mild opioid deprivation increases the degree that opioid-dependent outpatients discount delayed heroin and money. *Psychopharmacology* 163, 174–182. doi: 10.1007/s00213-002-1159-2

Gosling, S. D., Rentfrow, P. J., and Swann, W. B. Jr. (2003). A very brief measure of the big-five personality domains. *J. Res. Pers.* 37, 504–528.

Green, L., Fisher, E. B., Perlow, S., and Sherman, L. (1981). Preference reversal and self control: choice as a function of reward amount and delay. *Behav. Anal. Lett.* 1, 43–51. doi: 10.1901/jeab.1996.66-29

Green, L., Fristoe, N., and Myerson, J. (1994). Temporal discounting and preference reversals in choice between delayed outcomes. *Psychon. Bull. Rev.* 1, 383–389. doi: 10.3758/BF03213979

Green, L., Myerson, J., and McFadden, E. (1997). Rate of temporal discounting decreases with amount of reward. *Mem. Cogn.* 25, 715–723. doi: 10.3758/bf03211314

Jimura, K., Myerson, J., Hilgard, J., Braver, T. S., and Green, L. (2009). Are people really more patient than other animals? Evidence from human discounting of real liquid rewards. *Psychon. Bull. Rev.* 16, 1071–1075. doi: 10.3758/PBR.16.6.1071

Johnson, M. W., Bickel, W. K., Baker, F., Moore, B. A., Badger, G. J., and Budney, A. J. (2010). Delay discounting in current and former marijuana-dependent individuals. *Exp. Clin. Psychopharmacol.* 18, 99–107. doi: 10.1037/a0018333

Kaplan, B. A., Amlung, M., Reed, D. D., Jarmolowicz, D. P., McKerchar, T. L., and Lemley, S. M. (2016). Automating scoring of delay discounting for the 21-and 27-item monetary choice questionnaires. *Behav. Anal.* 39, 293–304. doi: 10.1007/s40614-016-0070-9

Kaplan, B. A., Lemley, S. M., Reed, D. D., and Jarmolowicz, D. P. (2014). *21- and 27-Item Monetary Choice Questionnaire Automated Scorers*. Lawrence, KS: University of Kansas.

Kirby, K. N., and Maraković, N. N. (1995). Modeling myopic decisions: evidence for hyperbolic delay-discounting within subjects and amounts. *Organ. Behav. Hum. Decis. Process.* 64, 22–30.

Kirby, K. N., Petry, N. M., and Bickel, W. K. (1999). Heroin addicts have higher discount rates for delayed rewards than non-drug-using controls. *J. Exp. Psychol. Gen.* 128, 78–87. doi: 10.1037//0096-3445.128.1.78

Lagorio, C. H., and Madden, G. J. (2005). Delay discounting of real and hypothetical rewards III: steady-state assessments, forced-choice trials, and all real rewards. *Behav. Processes* 69, 173–187. doi: 10.1016/j.beproc.2005.02.003

Lawyer, S. R., Williams, S. A., Prihodova, T., Rollins, J. D., and Lester, A. C. (2010). Probability and delay discounting of hypothetical sexual outcomes. *Behav. Processes* 84, 687–692. doi: 10.1016/j.beproc.2010.04.002

Loewenstein, G., and Prelec, D. (1992). Anomalies in intertemporal choice: evidence and an interpretation. *Q. J. Econ.* 107, 573–597.

Loewenstein, G., and Thaler, R. H. (1989). Anomalies: intertemporal choice. *J. Econ. Perspect.* 3, 181–193.

Mazur, J. E. (1987). "An adjusting procedure for studying delayed reinforcement," in *The Effect of Delay and of Intervening Events on Reinforcement Value*, eds M. L. Commons, J. E. Mazur, J. A. Nevin, and H. Rachlin (Mahwah, NJ: Lawrence Erlbaum Associates, Inc), 55–73. doi: 10.1016/j.beproc.2008.12.017

McClure, S. M., Laibson, D. I., Loewenstein, G., and Cohen, J. D. (2004). Separate neural systems value immediate and delayed monetary rewards. *Science* 306, 503–507.

Mischel, W., Shoda, Y., and Rodriguez, M. I. (1989). Delay of gratification in children. *Science* 244, 933–938.

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

O'Donoghue, T., and Rabin, M. (2015). Present bias: lessons learned and to be learned. *Am. Econ. Rev.* 105, 273–279.

Odum, A. L. (2011). Delay discounting: trait variable? *Behav. Processes* 87, 1–9. doi: 10.1016/j.beproc.2011.02.007

Odum, A. L., Baumann, A. A., and Rimington, D. D. (2006). Discounting of delayed hypothetical money and food: effects of amount. *Behav. Processes* 73, 278–284. doi: 10.1016/j.beproc.2006.06.008

Odum, A. L., Becker, R. J., Haynes, J. M., Galizio, A., Frye, C. C., Downey, H., et al. (2020). Delay discounting of different outcomes: review and theory. *J. Exp. Anal. Behav.* 113, 657–679. doi: 10.1002/jeab.589

Ohme, J., Araujo, T., de Vreese, C. H., and Piotrowski, J. T. (2021). Mobile data donations: assessing self-report accuracy and sample biases with the iOS screen time function. *Mob. Media Commun.* 9, 293–313.

Perry, J. L., Larson, E. B., German, J. P., Madden, G. J., and Carroll, M. E. (2005). Impulsivity (delay discounting) as a predictor of acquisition of IV cocaine self-administration in female rats. *Psychopharmacology* 178, 193–201. doi: 10.1007/s00213-004-1994-4

Peters, J., and Büchel, C. (2011). The neural mechanisms of inter-temporal decision-making: understanding variability. *Trends Cogn. Sci.* 15, 227–239. doi: 10.1016/j.tics.2011.03.002

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., and Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J. Appl. Psychol.* 88, 879–903. doi: 10.1037/0021-9010.88.5.879

Prelec, D., and Loewenstein, G. (1991). Decision making over time and under uncertainty: a common approach. *Manag. Sci.* 37, 770–786.

Schulz van Endert, T., and Mohr, P. N. (2020). Likes and impulsivity: investigating the relationship between actual smartphone use and delay discounting. *PLoS One* 15:e0241383. doi: 10.1371/journal.pone.0241383

Shefrin, H. M., and Thaler, R. H. (1988). The behavioral life-cycle hypothesis. *Econ. Inq.* 26, 609–643.

Smith, C. L., and Hantula, D. A. (2008). Methodological considerations in the study of delay discounting in intertemporal choice: a comparison of tasks and modes. *Behav. Res. Methods* 40, 940–953. doi: 10.3758/BRM.40.4.940

Statista (2021). *Instagram: Age and Gender Demographics*. Available Online at: https://www.statista.com/statistics/248769/age-distribution-of-worldwide-instagram-users/ [accessed November 24, 2021].

Tangney, J. P., Baumeister, R. F., and Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J. Pers.* 72, 271–324. doi: 10.1111/j.0022-3506.2004.00263.x

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Econ. Lett.* 8, 201–207.

Wilhelm, C. J., and Mitchell, S. (2009). Strain differences in delay discounting using inbred rats. *Genes Brain Behav.* 8, 426–434. doi: 10.1111/j.1601-183X.2009.00484.x

Wilmer, H. H., and Chein, J. M. (2016). Mobile technology habits: patterns of association among device usage, intertemporal preference, impulse control, and reward sensitivity. *Psychon. Bull. Rev.* 23, 1607–1614. doi: 10.3758/s13423-016-1011-z

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