

Digital Devices and Consumer Well-being

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Paper #1: : Technology-Mediated Social Risk-Taking: The Influence of Smartphone Use and Locus of Control.

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Paper #2: : The Role of Mobile Devices in Developing Child Financial Literacy

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Paper #3: Consuming and Sharing Information Without Regard for Reward? The Anatomy of Twitter Habits.

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Paper #4: Replacing Unwanted Smartphone Habits with Desirable Habits

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SESSION OVERVIEW

The rapid growth of mobile technology and its impact on consumer decision-making calls for actionable findings to improve consumers' good. Rather than offering a one-dimensional view of the relationship between digital technology and subjective well-being, we aim to provide a more nuanced perspective by surveying varying usage contexts, different sources of consumer heterogeneity and different aspects of well-being.

In this session, we share findings about how, for whom, and under what conditions, smartphone usage affects well-being, broadly construed, both positively or negatively. For instance, consumers are often confronted with risky social decisions, while online, that may lead to feelings of embarrassment and other negative consequences. As paper 1 explores, the use of smartphones as choice context can benefit certain consumers and lead to decreased social risk-taking behavior due to increased feelings of psychological ownership. Paper 1 demonstrates that consumers make less socially risky choices on smartphones rather than laptops when they have an external locus of control.

Mobile technology can also benefit the development of child financial literacy and financial well-being, as shown in the second paper employing objective field data from a mobile application company. Children can learn about the value of money by means of a mobile application which allows them to track allowances, record chores, and organize savings. As in papers 1, paper 2 demonstrates that there is considerable heterogeneity: children with high goal-striving tendencies tend to benefit the most.

Despite such benefits for social risk-taking and financial well-being, digital devices might also negatively impact certain consumers in particular contexts, as paper 3 demonstrates by analyzing objective *Twitter* data of 400 *Twitter* users employing a customized web-scraping technique. Highly habitual *Twitter* posters seem to be no longer responsive to feedback cues such as 'likes' in their prior tweets. Less frequent tweeters on the other hand, are changing their

tweeting rates in response to these rewards, and tweet less rapidly after receiving higher quantities of likes on recent tweets.

Finally, paper 4 provides a workable intervention for those consumers who would like to reduce their digital device usage by analyzing longitudinal mobile usage data measured via screen time tracking applications. For long-term goal achievement, using an incentive scheme which replaces excessive smartphone usage with a positive desirable habit (language learning or physical activity) is more effective than an incentive scheme that only aims to reduce undesirable technology usage. Furthermore, consumer heterogeneity plays an important role as this habit replacement process.

Together, the four papers present a comprehensive overview of how and for which consumers, smartphone technology can impact different aspects of wellbeing. At the end, Shiri Melumad will lead a discussion on the topic. We hope this special session will be insightful for audiences who are interested in consumer technology interaction, digital devices, and consumer welfare. We believe that it also speaks to the conference theme ("Spreading good WELL") by reflecting how digital devices impact consumers not always negatively but can also be leveraged to improve consumers' good.

Socially Safe on Smartphones: How Smartphone Use and Locus of Control Influence Social Risk Taking

EXTENDED ABSTRACT

Consumers make myriad social decisions on their smartphones, such as posting reviews, sharing photos with friends, and purchasing products that signal their identity and group membership both online and offline. The smartphone's influence on mental well-being (e.g., Lee et al., 2014), emotions (e.g., Melumad & Pham, 2020, Clayton et al., 2015), cognition (e.g., Ward et al., 2017), preferences (e.g., Song & Sela, 2022, Zhu et al., 2021) and behavior (e.g., Melumad et al., 2019; Mograbi, 2022) has received a substantial amount of attention. However, little is known about how smartphones affect social risk taking, defined as the decision to engage in behaviors that might put one's social standing at risk, elicit embarrassment, and ultimately affect consumer welfare (Krishna et al., 2019; Leary & Kowalski, 1997). In this paper, we examine how, and for whom, smartphone use affects social risk taking. Given that locus of control — the extent to which a consumer attributes outcomes of events to external factors rather than their own actions — has been shown to influence decision making and risk taking (e.g., Hashimoto & Fukuhara, 2004), we examine how the effect of smartphone use on social risk taking varies among consumers with differing locus of control orientations.

Social risk taking involves decision making for outcomes, which are uncertain. A negative outcome (e.g., a negative reaction from friends or family) would harm one's perceived social standing. In contrast, a positive outcome (e.g., a positive reaction from friends or family) would enhance one's perceived social standing. However, because consumers differ in the extent to which they perceive control over outcomes in their lives, certain individual characteristics play a central role in consumers' propensity to take social risks. Externally oriented consumers (i.e., externals), who believe outcomes in life are attributed to external factors rather than to their actions, tend to rely more on external cues to inform their decision making and may be inherently more sensitive to the contextual effects of device type

compared to internally oriented consumers (i.e., internals; Hashimoto & Fukuhara, 2004).

We suggest that externals experience lower self-efficacy in navigating social outcomes when making social decisions, driving their aversion to social risk taking. Since internals do not rely on contextual cues to the same extent, we find that their use of smartphones has little to no effect on their self-efficacy and social risk taking. Five studies support this proposition and show that externals (vs. internals) are less likely to take social risks when making social decisions on their smartphone compared with another device (e.g., their PC or a lab smartphone). On the other hand, internals show little difference in social risk taking when making social decisions between devices. Three of these studies are reported below.

In Study 1a ($N=236$, 48.3% female, $M_{age}=21.6$), we investigate whether smartphone use results in lower social risk taking for externals. We design a 2 (device type: smartphone vs. PC) $\times$ continuous (locus of control) mixed-design where participants completed the study via their PC or smartphone and self-reported their locus of control. Participants were instructed to imagine that they were playing a “Truth or Dare” game, designed to elicit embarrassment (Miller, 1992; Mandel, 2003). To measure social risk taking, we asked participants a series of eight binary questions, each of which offered a choice between a certain, safe option and an uncertain, risky option (Weber & Hsee, 1999). Across the eight questions, the risky option was held constant as a 50/50 chance of experiencing an embarrassment rated a 0 (no embarrassment) or a 10 (extreme embarrassment). The safe option varied from certain embarrassment ratings of 1 to 8. After completing the risk scale, participants answered questions aimed at capturing their locus of control (modified version of Levenson, 1981; 7-point scale). Our analysis revealed a significant interaction of device type and locus of control on social risk taking ($b=-.85$, $t=-2.57$, $p=.01$). Analysis of conditional effects confirmed that externals were less willing to take social risks in the smartphone condition compared to the PC condition ($M_{smartphone}=2.9$, $M_{PC}=4$, $p=.01$). However, internals did not show a significant difference between the two devices ($p=.27$).

In Study 3 ($N=186$, 59% female, $M_{age}=21.4$), we aimed to 1) test our proposed mechanism through self-efficacy and 2) rule out the smartphone’s functionality (e.g., form factor) as an explanation for our effects by manipulating smartphone ownership (own phone vs. lab phone). We replicated our interaction of device type and locus of control on social risk likelihood ($b=-.07$, $t=-2.01$, $p=.05$), where externals indicated a lower social risk likelihood on their own smartphone vs. a lab smartphone ($M_{own}=3.01$, $M_{lab}=3.35$, $p=.07$) while internals did not indicate a significant difference in social risk likelihood between the devices ($p=.29$). We also found a marginally significant index of moderated mediation ($b=.01$, 90% CI: $[-.03, -.001]$), with a marginally significant conditional indirect effect of smartphone use on social risk taking through self-efficacy for externals ($b=.07$, 90% CI: $[-.16, -.002]$) but not for internals ($b=.01$, 90% CI: $[-.01, .05]$). These findings suggest that social cues conferred by one’s own smartphone, and not the smartphone’s functionality, drive our effects.

In Study 4 ($N=597$, 68% female, $M_{age}=36.4$), we aimed to 1) test social risk taking within an online context, 2) unpack the role of self-efficacy by examining the role of perceived social support as an antecedent for self-efficacy. We again replicated our interaction of device type and locus of control on social risk likelihood ($b=.25$, $t=-2.74$, $p=.006$) and found a significant index of moderated serial mediation through perceived social support and self-efficacy ($b=.01$, 95% CI: $[-.02, -.001]$). Our analysis of conditional indirect effects shows that externals perceive less social support when

on their smartphones (vs. PC), driving a reduction in self-efficacy and, subsequently, social risk taking ($b=-.02$, 95% CI: $[-.05, -.003]$). Internals did not differ between the two devices ($b=.004$, 95% CI: $[-.10, .02]$). These results suggest that externals’ sensitivity to the decision context results in lower perceived social support when using a smartphone, driving a reduction in self-efficacy and social risk taking.

Consumers are often confronted with social decisions that may negatively impact their well-being. It is important for marketers and policymakers to understand the underlying mechanisms and contextual factors that drive a propensity to avoid such risk. Our results show that smartphones as the choice context reduces social risk taking because of lower self-efficacy. However, this effect is contingent upon consumers’ tendency to attribute outcomes in life to external factors rather than one’s own actions.

The Role of Mobile Devices in Developing Child Financial Literacy

EXTENDED ABSTRACT

In the last decade, mobile apps have become one of the most important marketing channels for many industries. In 2019, about 89% of all time spent on mobile devices in the U.S. is spent using different apps and about 72% of all retail and shopping-related electronic browsing is happening on the phone, rather than on desktops (Comscore 2019). What is particularly striking about mobile proliferation is that children too now spend a ton of their time on mobile. Recent research has shown that children are using smartphones from an early age with 60% of parents stating their kids started engaging with smartphones before the age of five (Pew Research 2020).

At a global level, research has shown that financial literacy is a massive issue that has not been clearly handled. In the US, many adults are unable to answer elementary-level questions about credit card use, compound interest, effects of inflation, or properties of stocks and bonds (Lusardi and Mitchell 2011; Lusardi and Tufano 2009). As well, adult education interventions are often ineffective considering financial behaviors (Fernandes, Lynch, and Netemeyer 2014).

Considering the combination of financial literacy concerns and the need to understand the benefits and drawbacks of mobile device use on consumers, we examine the role of mobile technology on child financial literacy and financial well-being. We partnered with a mobile app company designed to assist children in learning the value of money and which allows children to track their allowances, record chores, organize savings, etc.

Study 1 examines the effects of goal-striving on responsible financial behaviors. 306 children’s behavioral savings data from the app was combined with results from a survey we collected where goal-striving and items on financial literacy were measured. Goal-striving was measured using a set of established questions (Batty et al. 2015) and answered by a guardian. Financial literacy was measured using two questions, one on conceptual financial literacy, and a second on numerical financial literacy. Savings was operationalized as the amount each child had saved in the app at the time of data collection.

We find that children with higher goal-striving tendencies are more likely to have saved more money. Specifically, for each higher point on the goal-striving scale, a child would be expected to have saved 348 SEK more. Children that are more goal-striving are also significantly more likely to answer the question on conceptual financial literacy correctly, which in turn is associated with higher

spending behaviors. However, there was no statistically significant relationship between goal-striving and numerical financial literacy.

Study 2 assesses some long-term effects of setting goals on future savings behaviors. 2,500 children were randomly drawn where their goal-setting behaviors, their monetary transactions in and out from the app account, and descriptive demographics were collected. This was done so that we could connect the situations when children set up new goals and their causal effects on future savings balances. As the data was longitudinal, some inferences of cause and effect could be made. Specifically, because of the complex data structure, a hierarchical cross-effect continuous-time model was applied to estimate the future effects of setting goals on children's savings behaviors. The model also included control variables.

The model indicates that there is a significant cross-effect of goal-setting on later values of children's savings behaviors. Each time a child sets up a goal, they are more likely to show higher future savings behaviors. The effect of goals (and savings) is the strongest in the first few months following the activity, while the effect gradually decreases. Importantly, according to the results, the positive effect of goal-striving holds for several years ahead. In short, children engaging with goal-setting in the app are shown to save more of their money (versus consuming) in the future. This holds even when controlling for age and length of usage with the app, showcasing potential long-term benefits to using mobile devices for financial tracking and planning.

In Study 3, we model the effect of children engaging with the goal-setting function on future savings behaviors as well as the type of future purchases (real money spent).

To assess children's financially responsible behaviors, 2,291 children were randomly pulled from the database that were also using the app's Card function; a prepaid credit card specifically catered towards children. Data on these children's interaction with the app goal-setting function was provided. Responsible financial behaviors were operationalized using two main sets of measures: 1) the actual balance in the card wallet, 2) the type of spending. A higher balance in the card account is assumed to be more financially responsible. For the type of spending, measures were drawn from the type of merchants (retailers), based on their Merchant Category Codes (i.e., "restaurant," "toy store,"). These categories were coded into key dimensions: e.g., long-term investments, level of planning, hedonicity, social consumption. Again, the model included exogenous variables to control for age effects and the length of using the app.

The model indicates that there is again a significant cross-effect of children's engagement with the goal-setting functionality and downstream savings behaviors. When children set up goals, there is a positive effect to the system in that they keep more funds available from their savings account. The effect is stronger for older children than younger children. There is also an impact on the type of products purchased. As children set up more goals in the app, they are more likely to spend their money at merchants that sell products that are more of a long-term investment. Finally, there were some key associations with regards to the introduction of various new functions in the app. The introduction of a friends-sharing function to the app was significantly associated with higher savings, but also more social consumption. The introduction of educational chapters to the app was positively associated with higher levels of planning.

Based on the research thus far, several key takeaways become apparent. When children have tangible ways to organize and strive for financial goals, there are positive effects on their financial behaviors, which has potential long-term well-being implications.

Consuming and Sharing Information Without Regard for Reward? The Anatomy of Twitter Habits.

EXTENDED ABSTRACT

Two observational studies of *Twitter* users ($N=760$) examine information consumption and sharing behavior as it relates to rewards on online social media platforms. Our findings suggest that users with weak habits/lower frequency of sharing (Study 1) and consuming (Study 2) information online are more sensitive to potential rewards. These rewards include likes, replies, retweets from others (Study 1), and the content of the tweets they consume (Study 2). In comparison to less habitual sharers and consumers, strongly habitual and highly frequent sharers and consumers of information online were less responsive to rewards. These studies represent novel applications of existing neuroscientific, social psychological, and animal learning research to consumer behavior and the social media context.

Study 1 scraped the public tweeting data of 400 *Twitter* users using a customized web-scraping technique to monitor users' profiles for new tweets every 20 minutes during a week-long observation period. Because prior literature has found that strongly habitual Facebook posters are less sensitive to rewards, such as likes, on the platform than less habitual posters, we predicted that this would also be the case for *Twitter* users as well (Anderson & Wood, 2023). Our data confirmed our hypothesis that highly frequent posters do not change their tweeting rates in response to higher or lower quantities of likes and/or retweets in their prior tweets, which is consistent with the idea that these users have posting habits. Interestingly, less frequent tweeters did change their tweeting rates in response to rewards and tweeted less rapidly after receiving higher quantities of likes on recent tweets. These patterns held also when using participant-mean centered quantities of likes and sample-mean centered likes—which reflect relative reward perception, or reward prediction errors, defined here as the difference between actual quantities of rewards received and users' anticipated quantities of rewards received (based on Hackel & Amodio, 2018). These relationships between user habits, rewards, and tweeting rates also held when we used other reward measures in the same model, including retweets alone and the combined quantity of likes and retweets received.

The reward-sensitive behavior of the non-habitual posters is most similar to patterns observed in existing literature on foraging behavior—in the sense that we see these consumers discontinue behavior after achieving a desired quantity of rewards (Rudebeck & Izquierdo, 2022). Our second study builds on this observation of posting behavior, drawing on both literature on reward prediction errors and foraging, to test whether similar patterns exist in information consumption on *Twitter*.

Study 2 thus examines scrolling behavior, the primary mode of information consumption on *Twitter*. This study observed $N=360$ *Twitter* users (240 recruited from the USC subject pool, and 120 Prolific) while they scrolled pre-determined sets of tweets under three topics: USC (Subject Pool) and Entertainment (Prolific). These sets of tweets (scrolls) were constructed by first having groups of peers rate a large set of tweets on these topics for how interesting (rewarding) they each were, and then subsequently using both random selection and careful design to put tweets into a specific, reward-based order by the researchers. These peer ratings were later used to model scrollers' anticipated reward—part of reward prediction errors. Next, participants were randomly assigned to record themselves while scrolling through equally rewarding scrolls that were crafted by researchers to be consistently rewarding (all tweets about the same level or rewardingness) or intermittently rewarding (less rewarding tweets randomly interspersed with more rewarding ones).

Based on prior literature on reward learning in animals, we hypothesized that intermittently rewarding scrolls would cause non-habitual, reward-sensitive scrollers to scroll for longer than the consistently rewarding ones (Maki et al., 2012; Skinner, 1953). Habitual, reward-insensitive scrollers should scroll for a roughly equal amount of time regardless of whether they were assigned to the intermittent or consistent scrolling condition. Our results showed that this hypothesis was confirmed across topics. Less habitual scrollers also tended to stop scrolling after seeing more rewarding tweets, aligned with the foraging behavior observed among the non-habitual posters in Study 1. In addition, we showed that the reward prediction errors at the tweet level predicted scrolling behavior for non-habitual scrollers, but not for habitual ones.

In sum, these studies show similarities in how *Twitter's* reward structure builds habits to both consume and share information. Before forming habits, users engage in behavior consistent with foraging for rewards within the platform. These findings have relevance across many levels of business. Consumers can understand how *Twitter* initially motivates them and how their *Twitter* habits may cause them to be less sensitive to the content they consume or share (Ceylan et al., 2023). Managers and user experience/user interface designers can learn from our finding that *Twitter* users are more incentivized by intermittent rewards. This finding implies, for example, that optimizing for content to be consistently rewarding may not always be a good goal when designing social media platforms. Our findings suggest that both platforms and consumers must consider habits to fully understand or change behavior in the social media context.

These studies theoretically contribute to both the social psychological and neuroscientific literature on habit learning by studying intermittent vs. consistent rewards and reward prediction errors in the social media context, and by presenting novel evidence for the habit-forming effects of intermittent rewards in humans. These studies also add to the growing literature on habitual and repeated consumer behavior and suggest clear differences between the habitual consumption of information and non-habitual consumption of information that should be further investigated in future research.

Replacing Unwanted Smartphone Habits with Desirable Habits

EXTENDED ABSTRACT

Excessive smartphone usage has become a growing concern for many consumers across the world (Deloitte, 2019). Research has also pointed to negative associations between mobile screen time and academic performance (Lepp, Barkley, & Karpinski, 2015; Giunchiglia et al., 2018; Zimmermann, 2021), performance at work (Lanaj, Johnson, & Barnes, 2014; Liu, Ji, & Dust, 2020) as well as wellbeing (Lee et al., 2014; Volkmer & Lerner, 2019). While many consumers nowadays have the goal of reducing their mobile screen time, this goal is seldom achieved, arguably because smartphone usage is a highly habitual behavior (Anderson & Wood, 2021). Recent studies have found monetary incentives to be effective to encourage consumers to cut down on smartphone and social media consumption (Allcott et al., 2022; Collis et al., 2019). But a common problem of interventions using monetary incentives is that after a period of successful behavior change, people revert to their typical consumption pattern, a phenomenon labelled as the “triangular relapse pattern” (Wood & Neal, 2016).

Our research aims to provide a solution to this relapse pattern by testing the “dual-habit” intervention in the domain of mobile consumption. In this intervention, we aim to fill the time freed up by reducing a bad habit (i.e., excessive social media/smartphone usage)

by inculcating a good habit (i.e., learning a new language, increased physical activity). Specifically, by looking less at their phones, consumers free up considerable time throughout their day, which creates a void that needs to be deliberately filled with other activities, otherwise they might revert to the habitual phone-staring. We argue that consumers who manage to replace their mobile usage with an alternative habit, will be more likely to maintain a lower mobile usage in the long run, compared to those who only focus on reducing their excessive mobile usage without a replacement behavior.

Methodology and Results: In both studies, we used a pre-post longitudinal design and measured actual behaviors objectively (rather than relying on self-report). After a baseline period of 7 days, subjects completed an intervention phase of 20 days. This was followed by a post-treatment period of 13 days in Study 1 and 47 days in Study 2. We collected objective social media and Duolingo usage in Study 1, total screen time and step count in Study 2 using mobile phone applications (i.e., Screen Time App, Health App).

In study 1, subjects ($N=43$; 1,571 observations, 72% female; $\text{Mage}=21.6$, $\text{SD}=1.79$) were incentivized to achieve two different targets during the treatment period: Subjects could earn €1 per day if they reduced their social media usage by 30% (Single Target); OR they could earn €2 per day if they reduced their social media usage by 30% AND additionally increased their language learning time by 20 minutes in Duolingo (Dual Target). Subjects were free to choose whether they wanted to achieve both targets, only the single target, or neither.

On average, subjects decreased their social media usage and increased Duolingo usage during the treatment period with incentives (social media: $\beta=-0.532$, $p < .01$; Duolingo: $\beta=0.150$, $p < .01$) compared to the baseline. A panel regression analysis showed that subjects who achieved more dual-target days (instead of single-target days) tended to have a lower social media usage during the post-treatment period relative to their baseline ($\beta=-0.072$ (hour), $\text{SE}=0.024$, $p < .01$). We also found evidence that each additional day of achieving both targets instead of just one was associated with a significant decrease in participants' perceived smartphone addiction level ($\beta=-0.038$, $p < .01$).

In Study 2, a randomized controlled trial, we randomly assigned subjects ($N=110$; 4,098 observations, 58% female; $\text{Mage}=24.4$, $\text{SD}=3.53$) to two different conditions: dual-habit (DH) versus single-habit (SH) condition. SH subjects were incentivized with €2 per day if they lowered their baseline mobile screentime by 30%. DH subjects were incentivized with €2 per day if they lowered their baseline mobile screentime by 30% AND additionally walked 2,000 steps more than their baseline. A difference-in-difference regression analysis showed that during the incentivized phase, subjects in both SH and DH conditions decreased their usage by 1.434 hours ($p < .001$) and 1.055 hours ($p < .001$), respectively, compared to the C condition.

Because adherence is critical to habit formation, the effectiveness of the DH relative to SH intervention must be evaluated contingent on subjects' adherence to the respective treatment. With an instrumental variable regression analysis utilizing the treatment condition as the instrument for the endogenous adherence to the treatment, we show that subjects who achieved more dual-habit target days tended to reduce their screentime in the post-treatment period more than subjects who achieved more single-habit target ($\beta_{\text{dual}}=-0.23$ vs. $\beta_{\text{single}}=-0.13$; Wald χ^2 (1, 2722)=5.73, $p=.016$).

Our proposed dual-habit approach can be of interest to both policymakers and consumers. For policymakers, it can be a cost-effective tool as the dual-habit intervention not only encourages consumers to reduce their screentime, but also motivates them to

build a new beneficial habit such as exercising, a “2-for-1” approach that might deliver added long-term advantage over other single-habit interventions. For consumers, dual-habit intervention might offer a useful tool to those who seek to reduce their smartphone usage for good. By filling the void created by reducing mobile usage with other activities, consumers are more likely to maintain lower mobile usage in the long run. But adherence to the intervention plan is crucial for habit formation. Therefore, consumers may benefit from setting realistic goals, creating schedules, and finding ways to stay motivated and accountable to the intervention.

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