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Translating Strategies for Promoting Engagement in Mobile Health: A Proof-of-Concept Micro-Randomized Trial

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Abstract

Objective: Mobile technologies allow for accessible and cost-effective health monitoring and intervention delivery. Despite these advantages, mobile health (mHealth) engagement is often insufficient. While monetary incentives may increase engagement, they can backfire, dampening intrinsic motivations and undermining intervention scalability. Theories from psychology and behavioral economics suggest useful non-monetary strategies for promoting engagement; however, examinations of the applicability of these strategies to mHealth engagement are lacking. This proof-of-concept study evaluates the translation of theoretically-grounded engagement strategies into mHealth, by testing their potential utility in promoting daily self-reporting.

Methods: A micro-randomized trial (MRT) was conducted with adolescents and emerging adults with past-month substance use. Participants were randomized multiple times daily to receive theoretically-grounded strategies, namely reciprocity (the delivery of inspirational quote prior to

self-reporting window) and non-monetary reinforcers (e.g., the delivery of meme/gif following self-reporting completion) to improve proximal engagement in daily mHealth self-reporting.

Results: Daily self-reporting rates (62.3%; n=68) were slightly lower than prior literature, albeit with much lower financial incentives. The utility of specific strategies was found to depend on contextual factors pertaining to the individual's receptivity and risk for disengagement. For example, the effect of reciprocity significantly varied depending on whether this strategy was employed (vs. not employed) during the weekend. The non-monetary reinforcement strategy resulted in different outcomes when operationalized in various ways.

Conclusions: While the results support the translation of the reciprocity strategy into this mHealth setting, the translation of non-monetary reinforcement requires further consideration prior to inclusion in a full scale MRT.

Keywords

Engagement; Mobile Health (mHealth); Micro-Randomized Trial (MRT); Reciprocity; Reinforcement; [ClinicalTrials.gov: NCT03255317]

Introduction

Mobile technologies allow for accessible and cost-effective health monitoring and intervention delivery. Their widespread use, acceptability and convenience can help reduce barriers to health care access and utilization (Amico, 2015), and enhance scalability across geographic locations (Haberer et al., 2017). Mobile devices are also capable of giving round-the-clock, real-time reminders, intervention prompts and feedback. Smartphones and tablet computers are able to host applications (apps) with a multitude of capabilities (e.g., social networking, gaming) (Pellowski & Kalichman, 2012). A recent meta-analysis of mobile health (mHealth) intervention studies among youth concluded that mHealth is an effective modality for promoting health behavior change (Fedele et al., 2017).

Despite these advantages, engagement in mHealth tools is often too limited to support behavior change (Michie et al., 2017). Engagement is defined as a state of energy investment directed toward a focal task or stimulus (Shaw et al., 2019), which involves cognitive (e.g., attention), affective (e.g., positive feelings) and behavioral (e.g., participation) aspects (King et al., 2014). In mHealth interventions, the focus has been mainly on behavioral aspects of engagement (e.g., frequency, duration, or depth of usage) (Perski et al., 2016). Empirical evidence indicates that adequate usage of such tools is rare (Dobson et al., 2017; Saberi & Johnson, 2015), and least likely among those with poor self-reported health (Robbins et al., 2017). Thus, promoting adequate engagement with mHealth tools is of critical importance (Roberts et al., 2017).

While monetary incentives can increase mHealth engagement, relying on monetary incentives alone may backfire, dampening intrinsic motivations (Strang et al., 2016), leading to unintended consequences (e.g., inappropriate use of incentives increasing risk behavior; Kohler & Thornton, 2012) and undermining scalability. Hence, a richer toolset of incentives is clearly needed (Linnemayr & Thomas, 2016). Research in psychology, human computer interaction (HCI), and marketing highlights alternative engagement strategies, including

social influence tactics (Cialdini & Goldstein, 2004), behavioral economics principles (Haff et al., 2015), and gamification (e.g., Taylor et al., 2019). However, limited research attention has been given to optimizing theory-based engagement strategies in mHealth settings, where the goal is to engage individuals in their natural environment despite multiple demands competing for their time, effort and attention.

To address this gap, the current study was designed to build a research foundation for promoting engagement in mHealth tools. The mobile app used in the current study (Substance Abuse Research Assistant [SARA]) was motivated by evidence indicating that substance use among adolescents and emerging adults (A/EAs) is associated with the leading causes of morbidity and mortality (Hingson et al., 2017; Patrick et al., 2017). Increasing the frequency of self-reporting for substance use and related factors among youth is important from research (e.g., understand behavior change processes) and intervention perspectives (e.g., capitalize on the therapeutic gains of self-monitoring) (French & Sutton, 2010; Swendeman et al., 2015). Given research showing suboptimal engagement with self-reporting of substance use (Roberts et al., 2017), this proof-of-concept study examined the potential utility of theoretically-grounded strategies to promote engagement in daily mHealth self-reporting among substance-using A/EAs.

We begin by presenting a logic model (Figure 1) to help organize the engagement strategies integrated in SARA and then discuss scientific questions that motivate the investigation of two specific strategies. The first strategy-- *reciprocity*-- refers to the provision of a small unsolicited gift to capitalize on the innate psychological tendency to return favors and other acts of kindness (Cialdini, 2001; Perugini et al., 2003). The second strategy -- *non-monetary reinforcement* -- refers to providing conditional rewards that are hedonic in nature, based on entertainment and exploration (Coker et al., 2014). We then describe a micro-randomized trial (MRT) conducted with 68 A/EAs screening positive for binge drinking or marijuana use, who were instructed to self-report substance use and related factors via the SARA app for 30 days, and were micro-randomized daily to engagement strategies. We discuss results pertaining to the potential utility of reciprocity and non-monetary reinforcement in promoting mHealth self-reporting. The research questions and hypotheses motivating the MRT were specified a priori (Rabbi et al., 2017). Guided by the NIH Stage Model (Onken et al., 2014) and the Multiphase Optimization Strategy (MOST; Collins, 2018), we discuss implications for future research on promoting mHealth engagement.

A Logic Model for Integrating Engagement Strategies

Extant literature on engagement in learning activities (Butler & Nisan, 1986; Efklides, 2011), behavioral interventions (De Young, 2000; King et al., 2014; Lizardi & Stanley, 2010), and technology-based interventions (Cavanagh, 2010; Perski et al., 2016) highlight three interrelated constructs which determine the likelihood of engagement in an activity. *Need recognition*¹ reflects an individual's awareness of a discrepancy between his/her present state and a preferred future state (Allen et al., 2014; Fox & Miner, 1999);

¹Need recognition relates to the concept of self-discrepancy, which reflects a conflict or inconsistency between different aspects of the self (Higgins et al., 1986). A number of empirically-supported psycho-therapeutic approaches address such conflict, including Motivational Interviewing (Miller & Rollnick, 1991) and Acceptance and Commitment Therapy; see discussion in (Kelly et al., 2015).

ability, reflects the extent to which an individual has the knowledge, experience, skills and capacity to engage in the activity (Kleinginna & Kleinginna, 1981); and *motivation*, reflects the extent to which an individual is willing to engage (Rivis et al., 2011). The engagement strategies in SARA are consistent with the Need, Ability & Motivation (NAM) logic model.² To increase need recognition for self-reporting, SARA uses self-regulatory techniques (Carver & Scheier, 1982), including: setting clear goals for self-reporting, monitoring self-reporting via the app, and providing feedback. To enhance the participant's cognitive ability to engage in self-reporting, reminder notifications are provided to address forgetfulness. Finally, to enhance motivation to self-monitor, engagement is reinforced via a point system and a virtual aquarium, which starts empty, but displays more fish and treasures as the participant engages in daily self-reporting (see Rabbi et al., 2018). A more detailed conceptual diagram describing the different engagement strategies in SARA is provided in Rabbi et al (2017; Figure 3). Below, we provide the scientific rationale for testing two theoretically-grounded strategies for increasing motivation to engage: reciprocity and non-monetary reinforcement (Rabbi et al., 2017).

Reciprocity

The meta-norms of reciprocity are a suite of social rules maintaining that people should return favors and other acts of kindness (Gouldner, 1960). Performing a small, often unsolicited, favor can trigger these norms, increasing the likelihood that the recipient will later agree to a subsequent request from the favor-giver. Marketing strategies such as free gifts are common experiences for consumers, who may feel obligated to buy the product (Burger et al., 2009). Individuals may return favors out of concerns for what others may think of them (e.g., that they will be viewed ungrateful or as freeloaders; Cialdini, 2001) and/or because they internalize the reciprocity norms as a personal standard (Perugini et al., 2003). Hence, people feel good about themselves when they return favors, and chastise themselves when they fail to reciprocate.

Empirical evidence indicates that receiving help, gifts, favors, or concessions motivates people to reciprocate (Cialdini, 2001; Cialdini & Goldstein, 2004), including in human-computer interactions (Fogg, 2002; Fogg & Nass, 1997), human-robot interactions (Lee & Liang, 2016), and technology-facilitated social interactions (Parsons et al., 2019). However, no attempt has been made to investigate whether the norms of reciprocity can be capitalized on to increase mHealth engagement. In SARA, the provision of a small unsolicited reward was operationalized by offering an inspirational quote two hours prior to the start of the self-reporting window. Inspirational quotes were selected because (a) they are non-monetary in nature; and (b) preliminary formative research indicated that this type of content is valued by the target population (Rabbi et al., 2018). We posed the preliminary hypothesis:

H1³ : Offering (compared to not offering) a small, unsolicited reward in the form of an inspirational quote increases the likelihood of self-reporting on the current day.

²Related models exist, such as the COM-B system (Michie et al., 2011) for understanding behavior.

³Hypotheses 1, 2 and 3 were pre-specified in Open Science (Rabbi et al., 2017). H1 and H2 were specified as primary hypotheses, and H3 was specified as one of two secondary hypotheses.

Non-Monetary Reinforcement

Grounded in behavioral theory (i.e., operant conditioning), reinforcement — defined as “the process in which the occurrence of a behavior is followed by a consequence that results in an increase in the future probability of the behavior” (Miltenberger, 2011, p. 513) — is a well-established method for enhancing compliance (Shelton & Levy, 1981). A positive reinforcer is a stimulus that increases future behavior. In psychotherapy and coaching, verbal praise is a common reinforcer (Hancock, 2000), which does not have to involve actual social presence (i.e., a therapist) to be effective; Fogg (2002) found that a single dialog box praising the individual can enhance engagement. For a reinforcer to be effective, it should occur immediately after the target behavior (Miltenberger, 2011), which is easily accomplished in mHealth (Lent, 2017), and involve a greater magnitude for more complex behaviors (McPherson et al., 2018).

We tested two forms of non-monetary reinforcers: *entertaining content*, operationalized as a meme or an animated gif (funny or inspirational), and *personalized information*⁴, operationalized as visual data summaries. The first form is based on literature in positive psychology (e.g., Fredrickson, 2004) and learning (e.g., Pekrun, 2006) which posits that positive emotions facilitate increased effort, widening attention, promoting intrinsic motivation, and facilitating the use of flexible cognitive strategies (e.g., planning). Although offering mHealth content that promotes positive emotions could reinforce activities that require low effort (e.g., daily self-reporting), this has not been empirically established. The second form is based on research in the area of cognitive and social psychology (Brown & Dutton, 1995; Hull et al., 1988) which indicates that people strive to manage uncertainty by seeking and attending to information about themselves (Derricks & Earl, 2019; Leonardelli & Lakin, 2010; Van den Bos, 2009). Although people are interested in receiving personalized data (Rabbi et al., 2018; Singh et al., 2016), it is unclear whether such information reinforces mHealth self-reporting. Thus, we pose the preliminary hypotheses:

Offering (compared to not offering) a non-monetary reinforcer in the form of entertaining content (H2³); or in the form of personalized information (H3³) immediately following self-reporting, increases the likelihood of self-reporting on the next day.

Indicators of Vulnerability and Receptivity as Moderators

Organizing frameworks for constructing mHealth interventions emphasize the importance of delivering intervention prompts (e.g., cues to induce desired responses) (Raes et al., 2012) not only when the individual is vulnerable, but also in a manner that minimizes disruptions, that is, only when the individual is receptive. *Vulnerability* refers to the person’s transient tendency to experience negative outcomes (hence indicating need for an intervention), and *receptivity* refers to the person’s transient tendency to receive, process, and use intervention prompts (Nahum-Shani et al., 2015). In the context of enhancing mHealth engagement, vulnerability can be conceptualized as conditions that represent increased risk for disengagement, indicating need for an engagement strategy. Receptivity can be conceptualized as conditions in which a particular strategy is likely to increase

⁴Personalized information is labeled ‘life insights’ in previous descriptions of this study’s protocol.

engagement. Limited research attention has been given to identifying states of vulnerability to disengagement and receptivity to engagement strategies (Morrison et al., 2017).

Here, we explored four moderators (which were specified as covariates a priori: Rabbi et al., 2017) to identify the conditions in which individuals might be more vulnerable to disengagement, and more receptive to engagement strategies. With respect to vulnerability, two moderators were considered: prior self-reporting and app usage for other reasons (i.e., outside of self-reporting). Empirical evidence suggests that low engagement with mHealth technology increases the risk for future disengagement (Simblett et al., 2018), indicating the need for an engagement strategy (Karekla et al., 2019). Thus, mHealth prompts containing engagement strategies may be more effective if the individual did not self-report in the previous day or did not use the mobile app for other reasons. Regarding receptivity, two moderators were considered: day of the week (weekdays vs. weekend), and whether support was previously provided by study staff. Prior work suggest that individuals are more receptive to mobile prompts during the weekends (Bidargaddi et al., 2018) and human contact increases accountability and motivation (Karekla et al., 2019; Mohr et al., 2011), hence facilitating receptivity to prompts. Thus, prompts containing engagement strategies may be more effective during the weekend and if human support (e.g., reminders) was provided (here, by study staff).

H4: The effects of the engagement strategies (reciprocity and non-monetary reinforcement) on self-reporting are amplified under conditions that represent vulnerability to disengagement (i.e., no prior self-reporting or app usage for other reasons) and receptivity to engagement strategies (i.e., during the weekend and after receiving support from study staff).

Method

Study Design

This proof-of-concept study employed a micro-randomized trial (MRT) – an experimental design for optimizing mHealth interventions (Liao et al., 2016). This study was intended as an early check on translating theoretically-based engagement strategies to a particular mHealth setting. These activities are consistent with *Stage I* of the NIH Stage Model (Onken et al., 2014), which focuses on intervention creation, refinement and preliminary testing, as well as with the *preparation* phase of the Multiphase Optimization Strategy (MOST) (Collins, 2018), which focuses on laying the groundwork for optimizing a multi-component intervention. Here, optimization refers to gathering information to decide what set of components to include and how in order to comprise an effective and practical mHealth intervention, prior to evaluating its effectiveness relative to control (Collins, 2018). Guided by these frameworks, the MRT was employed to prepare for a fully powered optimization MRT, by testing the potential utility of two theoretically-grounded strategies (reciprocity and non-monetary reinforcers) in promoting mHealth engagement.

Participants

Participants were recruited and screened in the University of Michigan Hospital Pediatric and Adult Emergency Departments. The study was approved by the Institutional Review

Board of the University of Michigan (HUM00121553) and is registered at [ClinicalTrials.gov \(NCT03255317\)](https://clinicaltrials.gov/ct2/show/study/NCT03255317). Individuals were eligible for screening if they were 14–24 years old, understood English, were medically stable, able to provide informed consent or assent, and were accompanied by a parent or guardian (if 17 years old or younger). Screened individuals were eligible for the MRT if they had access to a mobile phone (Android or an iPhone) at enrollment and if they screened positive for past-month binge drinking (4 drinks for females and 5 drinks for males) and/or past-month marijuana use (without a medical marijuana card).

Procedures

Recruitment: Incoming admissions were reviewed (August 2017 - February 2018) to identify patients aged 14 to 24 who met inclusion criteria to approach (Figure 2).

Participants (n=271, 85.2%) completed consent/assent and a screening survey on a tablet assessing demographics, past-month health behaviors (e.g., alcohol and marijuana use) and cell phone capabilities (see details in Rabbi et al., 2018). Participants received a small gift valued at US \$1.00 (e.g., headphones, water bottle). Those who met substance use and cell phone inclusion criteria (n=111; 40.9%) were eligible for the MRT, and 74 (66.6%) consented/assented, of which 68 were able to be included in the analyses (ages 17–24), and 59 (79.7%) completed a one-month follow-up. For this proof-of-concept study, recruitment continued until project funds were spent.

Intake session: Participants enrolled in the MRT completed a baseline survey assessing substance use and motivation to reduce alcohol and marijuana (see Rabbi et al., 2018), provided their contact information, installed the SARA app, and received US \$20.

Micro-randomizations: Participants started a 30-day MRT, where they were asked to use the SARA app to complete one survey and two active tasks between 6pm and midnight daily. The present analytical sample comprised the 68 (91.9%) participants who installed the SARA app and completed at least one daily survey. To investigate the utility of reciprocity, participants were randomized at 4pm each day with a fixed 0.5 probability to either a prompt (via a push notification) containing an inspirational quote or no prompt. To investigate the utility of non-monetary reinforcement, each day, if the participant completed the survey, they were randomized with a fixed 0.5 probability to either a reinforcer in the form of entertaining content or no reinforcer, and if the participant completed the active tasks they were randomized with a fixed 0.5 probability to either a reinforcer in the form of personalized information, or no reinforcer. Study staff who had contact with participants were blinded to the random assignments.

One-month follow-up interview: Approximately one month after the intake visit, participants completed a follow-up assessment (all by telephone except 1 in-person), which included the baseline measures, a 30-day Timeline Follow Back calendar to capture alcohol and marijuana consumption (Hoeppner et al., 2010), and questions to capture user experience and acceptability of the SARA app (Stoyanov et al., 2015). Participants received a US \$30 electronic gift card of their choice (e.g., Amazon, Starbucks or Netflix).

Mobile-based self-reporting: The SARA app collects data via two active tasks (Research Kit, 2018) and daily surveys. The spatial memory task displays a random sequence of five seashells that light up in a 2-dimensional grid of nine seashells and asks participants to repeat the sequence. The reaction time task includes two buttons that participants are asked to tap alternately for 10 seconds. These tasks were selected given that spatial memory and reaction time may vary depending on substance use-related intoxication. The daily survey included 7 questions about factors associated with substance use, such as stress level, loneliness, and amount of free time. On Sundays, the survey included 14 additional questions about substance use and motives in the past week (see Rabbi et al., 2018 for details). Participants were asked to complete the daily survey and active tasks between 6pm and midnight in order to provide (a) sufficient time for self-reporting; (b) an opportunity for participants to reflect on most of the day while responding to the survey, and (c) an opportunity to capture intoxication via active tasks since substance use among youth typically occurs in the evening (Wray et al., 2014).

Contact by study staff: Contact by study staff was provided between 9pm – 10pm each night based on non-completion using a pre-specified message template (see Rabbi et al., 2018); thus, these reminders were not randomized. Specifically, a text message reminder was sent following two days of non-completion of the daily survey or active tasks. If non-completion continued for three additional days, a second text message was provided. After 7 consecutive days of non-completion, participants received a phone call from study staff. Occasionally, study staff sent reminders via email or private social media messages based on participants' preference, or if they had an out-of-service cell phone number, or had been nonresponsive to previous texts and phone calls. Text messaging and phone calls stopped if participants neither responded nor self-reported for 3 weeks (n=6), or if a participant asked to be removed from the study (n=1).

Minimal financial incentives: Participants earned US \$1 for every 3 consecutive days of daily self-reporting, and 50 cents for completing the longer Sunday survey. The rationale for including minimal financial incentives along with a non-monetary intervention is provided in Rabbi et al. (2018). For a 90% completion rate, most participants would earn US \$12 or less over the 30-day study (US \$13 if completion rate is 100%). This is a fraction of what substance use studies typically pay for daily self-reporting (e.g., US \$2–5 per day) (Bonar et al., 2018; Buu et al., 2017; Dworkin et al., 2017; Heron et al., 2019).

Randomized engagement strategies: The MRT investigated two engagement strategies; both were developed in a prior user-centered design process (see Rabbi et al., 2018). *Reciprocity:* At 4pm every day (two hours before the self-reporting window opened), participants were randomized to either a prompt containing an inspirational quote or no prompt. This timing was selected (a) to accommodate the typical daily routine of A/EAs (e.g., they may be more likely to attend to a notification after school hours); and (b) to be sufficiently close to the start of the self-reporting window (6pm). The inspirational quotes (i.e., song lyrics and celebrity quotes) were selected by undergraduate research assistants to make them age-appropriate. *Non-monetary reinforcement:* This strategy was operationalized and tested in two ways. First, upon completion of the daily survey, participants were

randomized to either a non-monetary reinforcer in the form of entertaining content or no reinforcer. The reinforcer included a meme or an animated gif, intended to be either funny or inspirational. This content was generated via Amazon's Mechanical Turk, and selected by undergraduate research assistants. Second, upon completion of the daily active tasks, participants were randomized to either a non-monetary reinforcer in the form of personalized information or no reinforcer. The reinforcer included a visual summary line graph of past seven days of data (e.g., stress, tapping speed). Both reinforcers were iteratively developed and preliminary tested prior to the MRT, with initial results indicating that they were both well liked and perceived as rewarding by the target population (Rabbi et al., 2020).

Measures

Feasibility: Building on prior work (Bonar et al., 2018; Stoyanov et al., 2015), feasibility was measured by: (1) completion of daily surveys, weekly surveys and active tasks; (2) amount of money earned during the 30-day MRT; and questions in the 1-month follow-up, including (3) subjective engagement measured by ratings of “fun” and “interesting” (Likert scale: 0=Not at all, 1=A Little, 2=Somewhat, 3=Moderately, 4=Very much so), and the age-appropriateness of content (Likert scale: 0=Not at all to 2=Very much); (4) acceptability of the inspirational quotes, memes/gifs, and personalized information (Likert scales: 1=Strongly dislike to 5=Strongly like); (5) subjective burden, measured by ratings of “easy to use” (Likert scale: 0=Not at all to 4=Very much so); frequency of technical problems (range: 0=Never to 3=Regularly); and (6) satisfaction, measured by preference to self-report using the app, phone or text message surveys, or either; and overall app rating (scale: 1 to 5 stars in 0.5 star increments).

Proximal self-reporting (proximal outcome): To test the effect of reciprocity, the proximal outcome is current day self-reporting—a binary indicator for whether (=1) or not (=0) the survey or the active tasks were fully completed on the same day. To test the effect of non-monetary reinforcement, the proximal outcome is next day self-monitoring-- a binary indicator for whether (=1) or not (=0) the survey or active tasks were completed on the following day.

Covariates/Moderators: Consistent with the Open Science registration (Rabbi et al., 2017), the covariates are as follows. *Prior day self-reporting:* a binary indicator for whether (=1) or not (=0) the survey and/or active tasks were completed in the prior day. *Prior app usage for other reasons:* a binary indicator for whether (=1) or not (=0) the app was used for activities unrelated to survey or active tasks completion prior to randomization (e.g., opening the app to look at the virtual aquarium or unlock a fish). For the analyses of reciprocity, this indicator was calculated based on the 72 hours⁵ prior to micro-randomization to employing (vs. not employing) the strategy. For the analyses of non-monetary reinforcement, this indicator was calculated based on the 80 hours⁵ prior to micro-randomization to employing

⁵These covariates were pre-specified while the study was underway and the study data was blinded from the team. Decision concerning the choice of these covariates as well as the time windows (e.g., 72 hours) were informed by research team consensus. In particular, these covariates were intended to be proxies for prior engagement. The team selected time windows that were long enough to capture engagement while short enough to avoid introducing excessive measurement error in the proxy.

(vs. not employing) the reinforcer. *Prior staff contact*: logs of staff emails, messages and phone calls were used to create a binary indicator for whether (=1) or not (=0) the individual was contacted prior to randomization. For reciprocity analyses, this indicator was calculated based on the 24 hours⁵ prior to micro-randomization to employing (vs. not employing) the strategy. For non-monetary reinforcement analyses, this indicator was calculated based on the 30 hours⁵ prior to micro-randomization to employing (vs. not employing) the reinforcer. *Weekend vs. Weekdays*: A binary indicator for whether (=1) or not (=0) the day of the week is a weekend (Saturday or Sunday).

Analytic Plan for MRT Data

The MRT data was analyzed with a generalization of regression specifically developed to ensure unbiased estimates of causal effects of time-varying treatments (Boruvka et al., 2018; Liao et al., 2016). These analyses pool time-varying, longitudinal data across participants. Here, this regression-based approach is used with a log-link function to accommodate the binary outcome. The causal effect among available participant days is expressed on the “risk-ratio” scale, namely on a scale that measures the probability (“risk”) of proximal self-reporting when an engagement strategy was employed, divided by the probability of proximal self-reporting when the engagement strategy was not employed. The pre-specified analytic plan (Rabbi et al., 2017) proposed to consider all participant days as available for the reciprocity strategy, all participant days in which the daily survey was completed as available for the entertaining content reinforcer, and all participant days in which the active tasks were completed as available for the personalized information reinforcer. Here, availability refers to days in which it is feasible and appropriate to deliver the strategy (see Boruvka et al., 2018; Klasnja et al., 2015). However, due to unanticipated technical issues (e.g., software bugs), there were days in which the delivery of the strategies could not occur. Those participant days were considered unavailable in the current analyses (see Yap et al., 2020a for details regarding the number of unavailable days for each strategy).

To test the effect of reciprocity, proximal self-reporting refers to the current day; whereas, to test the effect of non-monetary reinforcement, proximal self-reporting refers to the next day. Separate analyses were conducted to test the main effects of reciprocity (H1), the entertaining content reinforcer (H2), and the personalized information reinforcer (H3) on proximal self-reporting (see Table 1). For reciprocity, the risk-ratio will be greater than 1 if offering (vs. not offering) a prompt containing an inspirational quote has a causal effect on the probability of current day self-reporting. For non-monetary reinforcement, the risk-ratio will be greater than 1 if offering (vs. not offering) the reinforcer after survey completion (for entertaining content) or active tasks completion (for personalized information) has a causal effect on the probability of next day self-reporting. Moderators (H4) were tested separately for reciprocity and the two non-monetary reinforcers by extending the models used for H1, H2, and H3 to include covariates intended to investigate moderation of the causal effect of employing vs. not employing the strategy (Table 2). All analyses controlled for covariates expected to be highly correlated with self-reporting (i.e., prior day self-reporting, prior app usage for other reasons, and prior staff contact). These covariates were chosen to reduce the noise in the effects of engagement strategies (see pre-specified data analytic plan in Open Science (Rabbi et al., 2017)).

Since some participants were recruited after 4pm and could not be randomized to reciprocity until the second day of the MRT, we excluded data from the first day of the MRT (i.e., 29 possible days in analyses). Random assignments were missing for some participants on available days (i.e., 6, 13 and 22 participants with a total of 108, 21, and 37 days missing random assignments for reciprocity, entertaining content, and personalized information, respectively) due to technical issues (e.g., software bugs). All analyses were performed using complete case data, excluding days with missing random assignments. In sensitivity analyses, we also report the results based on a summary (Little & Rubin, 1987) of 10 datasets in which the missing value was multiply imputed with one of the two options under consideration (e.g., reciprocity prompt or no prompt) with 0.5 probability. Details regarding missing data are provided in Yap et al. (2020a).

Results

Sample Characteristics

Participants were, on average, 20.6 years old ($SD = 2.1$ years; range 17–24); 54.4% female, and 70.6% Caucasian. 69.1% had some college and 83.8% had an iPhone. At baseline, substance use was: 47.1% binge drinking only, 23.5% marijuana use only, and 29.4% both.

Feasibility

Participants completed an average of 60.3% of daily surveys ($M=18.1$, $SD=9.2$), 55.3% of active tasks ($M=16.6$, $SD=9.5$) and 75.0% of Sunday surveys ($M=3.0$, $SD=1.2$). On average, participants earned a total of \$6.24 ($SD=\3.83, $\text{min}=\$1.00$, $\text{max}=\$13.00$) for self-reporting. Most rated SARA as at least somewhat fun (76.3%) and interesting to use (72.9%). Almost all participants (96.6%) found the app to be somewhat or very age appropriate. Most liked or strongly liked the inspirational quotes (62.3%) and the personalized information (66.0%). However, less than half of participants (46.0%) liked or strongly liked the memes/gifs. In terms of burden, although nearly all participants perceived SARA as at least somewhat easy to use (96.6%), 38.0% had periodic or regular technical problems. Most participants would prefer using SARA to complete surveys, compared to phone-based (79.7%) or text message-based surveys (71.2%), and most (72.9%) rated SARA as 4.0 stars or higher.

MRT Results

Regarding reciprocity (Table 1), the results indicate that on average individuals are 5% more likely ($\text{Est} = \exp(.05)=1.05$; 95% CI: [.97, 1.13]) to self-report on the current day if an inspirational quote was offered at 4pm versus when not offered. However, there was insufficient evidence to reject the null hypothesis stating that there is no effect of this strategy. Regarding non-monetary reinforcement (Table 1), on average, individuals are 4% less likely ($\text{Est} = \exp(.04)=.96$; 95% CI: [.88, 1.04]) to self-report on the next day when entertaining content was offered after survey completion, versus when not offered. Moreover, on average individuals are 2% less likely ($\text{Est} = \exp(-.02)=.98$; 95% CI: [.90, 1.06]) to self-report on the next day when personalized information was offered after completion of active tasks, versus when not offered. However, there was insufficient evidence to reject the null hypotheses stating that these non-monetary reinforcers have no effect on next day self-reporting. In supplementary analyses, we found no evidence of

sex differences or day-of-study differences in the effects of reciprocity and non-monetary reinforcement (Yap et al., 2020b)

The moderators' analysis (Table 2) indicate that the effect of reciprocity varies depending on whether this strategy was employed during the weekend vs. weekdays (interaction estimate=.16; $p < .05$), and whether or not the individual used the app for matters unrelated to self-reporting in the past 72 hours (interaction estimate=-.27; $p < .10$). Employing (vs. not employing) reciprocity results in only 1% ($exp(.01)=1.01$; *ns*) greater likelihood of current day self-reporting during week days, yet in 18% ($exp(.17)=1.18$; $p < .05$) greater likelihood during weekends. Additionally, employing (vs. not employing) this strategy results in only 2% greater likelihood ($exp(.02)=1.02$; *ns*) of current day self-reporting if the individual used the app for reasons unrelated to self-reporting, yet in 35% ($exp(.30)=1.35$; $p < .10$) greater likelihood if they did not use the app for reasons unrelated to self-reporting. Effect moderation was not found statistically significant with respect to the other two candidate moderators.

Regarding non-monetary reinforcement, the moderators' analysis indicated that the effect of offering (vs. not offering) entertaining content immediately after current day survey completion varies based on prior day self-reporting (interaction estimate=.31; $p < .05$). It is estimated that offering (vs. not offering) this reinforcer immediately following current day (t) survey completion results in 1% ($exp(.01)=1.01$; *ns*) greater likelihood of next day ($t+1$) self-reporting if the individual self-reported in the prior day ($t-1$), yet in 25% less likelihood of next day self-reporting ($exp(-.29)=-.75$; $p < .05$) if the individual did not self-report in the prior day. Effect moderation was not found statistically significant with respect to the other three candidate moderators.

Lastly, the effect of offering (vs. not offering) personalized information after active tasks completion varies based on prior day self-reporting (interaction estimate=-.40; $p < .01$) and prior staff contact (interaction estimate=.20; $p < .05$). Offering (vs. not offering) this reinforcer after current day (t) task completion results in 9% ($exp(-.10)=-.91$; $p < .05$) less likelihood of next day ($t+1$) self-reporting if the individual self-reported in the prior day ($t-1$), yet 36% ($exp(.31)=1.36$; $p < .05$) greater likelihood if they did not self-report in the prior day. Next, offering (vs. not offering) this reinforcer after current day (t) task completion results in 9% ($exp(-.10)=-.91$; $p < .05$) less likelihood of next day ($t+1$) self-reporting if the individual did not receive staff contact prior to randomization, yet in 10% ($exp(.10)=1.10$; *ns*) greater likelihood if they received staff contact prior to randomization. Effect moderation was not statistically significant with respect to the other two candidate moderators.

Discussion

This study represents an important step in closing a practical and theoretical gap relating to the translation of theoretically-grounded engagement strategies into mHealth. Overall, the results provide initial support for the utility of theoretically-grounded strategies in promoting mHealth engagement.

Rates of daily self-reporting (e.g., 62.3% overall; 60.3% daily surveys (Mon-Sat); 75% weekly surveys) were somewhat less than previous ecological momentary assessment (EMA) studies with substance users, albeit with much lower financial incentives. A meta-analysis of EMA compliance among substance users of all ages showed that the pooled estimate was 70.8%; however, studies of A/EAs often find rates of 60–65% (Bonar et al., 2018; Buckner et al., 2012; Newcomb, Swann, Estabrook, et al., 2018; Newcomb, Swann, Mohr, et al., 2018; Shorey et al., 2014; Shrier et al., 2018). Our findings are particularly promising given that the average amount earned ($M=\$6.24$, $SD=\$3.83$, $\text{min}=\$1.00$, $\text{max}=\$13.00$) was a fraction of typical compensation provided, potentially reflecting the utility of the non-monetary engagement strategies in SARA. In addition to improved functionality, future iterations will attempt to improve non-monetary engagement features in SARA to reach 80% completion.

Findings from the MRT were supportive of the translation of reciprocity into SARA. Specifically, individuals were on average 5% more likely to self-report on the current day when a prompt containing an inspirational quote was offered (vs. not offered) prior to the start of the self-reporting window. Although this main effect was not statistically significant, it is higher in magnitude compared to the main effect (3.9% greater likelihood) found in an MRT study testing the utility of a prompt containing a tailored health message (vs. no prompt) on proximal engagement in self-reporting (Bidargaddi et al., 2018). Moreover, the positive effect of reciprocity was amplified under conditions that represent receptivity to mobile-based prompts (i.e., 18% greater likelihood during the weekend) and vulnerability to disengagement (i.e., 34% greater likelihood when employed following no app usage for other reasons). These findings are consistent with acceptability ratings and positive comments about these messages, with preference for greater personalization.

Concerning the translation of non-monetary reinforcement into SARA, findings from the MRT were not supportive of using entertaining content to operationalize this strategy. Individuals were on average 4% less likely (albeit not statistically significant) to self-report on the next day ($tt+1$) when a non-monetary reinforcer in the form of entertaining content was offered (vs. not offered) immediately following current day (tt) survey completion. This negative effect was found to be substantially amplified under conditions that represent vulnerability to disengagement. Specifically, if individuals did not self-report on the previous day ($tt-1$), offering entertaining content immediately following current day (tt) survey completion resulted in 25% less likelihood of self-reporting on the next day ($tt+1$), compared to not offering this reinforcer. These findings were consistent with acceptability ratings, with slightly less than half of participants liking the memes/gifs, and with the mix of positive and negative comments. In fact, some participants noted that the inspirational meme/gifs were better than the humorous ones, which were not viewed as particularly funny. Although we vetted the memes/gifs with similar-aged youth, and despite preliminary testing indicating that youth liked and perceived the memes/gifs as rewarding (Rabbi et al., 2020), the results suggest that this type of content may have a short shelf life, may be ineffective due to the high circulation in daily life, and/or would benefit from greater personalization due to individual differences.

Findings were more supportive of operationalizing non-monetary reinforcement in the form of personalized information. On average individuals were 2% less likely (albeit not statistically significant) to self-report on the next day when this reinforcer was employed (vs. not employed). However, this effect was positive under conditions that represent vulnerability to disengagement (i.e., 36% greater likelihood of next day self-reporting, if no self-reporting on prior day) and receptivity to mobile-based prompts (i.e., 10% greater likelihood of next day self-reporting under prior staff contact). These findings are consistent with acceptability ratings and comments suggesting that participants generally liked the personalized information. However, the effect of this reinforcer was negative under conditions that represent low vulnerability to disengagement (i.e., 9% less likelihood of next day self-reporting, if self-reporting on prior day) and less receptivity to mobile-based prompts (i.e., 9% less likelihood of next day self-reporting, if no prior staff contact). It is possible that when participants were engaged (i.e., self-reported in the prior day and did not require staff contact) they were irritated by the use of personalized information as a reinforcer. This explanation is consistent with acceptability ratings indicating that two-thirds liked or strongly liked the personalized information, and with comments indicating they wanted cumulative information available on demand (rather than contingent on self-reporting), similar to other mobile applications (e.g., steps in Fitbit). Future studies testing preferences for personalized information could also examine the potential benefits or harms of summaries regarding improvement vs. a decrement in engagement over time.

Although none of the engagement strategies were found to have a statistically significant main effect, significant and relatively large effects were found under specific conditions representing risk for disengagement and receptivity to mobile-based prompts. These findings may reflect the nature of mHealth intervention prompts, which are delivered in the individual's natural environment. In real-life settings, a complex constellation of stable and dynamic contextual factors may influence the extent that the individual can pay attention to and act on the prompt (Nahum-Shani et al., 2018). Given that the main effect is an average effect over time and over any other contextual factors, it is possible that the investigation of contextual moderators may be more informative in efforts to optimize mobile-based engagement prompts.

Contrary to expectation, we found no evidence that the effect of reciprocity is moderated by prior day self-reporting and staff contact, as well as no evidence that the effect of non-monetary reinforcement is moderated by weekend (vs. weekdays) and prior app usage for other reasons. While these results may suggest that indicators of vulnerability and receptivity which are relevant for reciprocity are less relevant for non-monetary reinforcement and vice versa, a full-scale study is required to validate these results and draw practical and theoretical conclusions.

Several limitations require acknowledgement. First, minimal financial incentives were provided in what is fundamentally a non-monetary intervention; this can have implications on the external validity of the study. Future studies should systematically investigate whether the results of the current study can be generalized to other settings, including those in which no financial incentives are provided. Second, future research should investigate whether the effects of reciprocity and non-monetary reinforcement vary depending on the type of task

participants are asked to perform (e.g., time to complete, difficulty, frequency and stigma associated with the behaviors participants are asked to self-report). Third, the utility of non-monetary reinforcers in SARA may be improved by considering alternative reinforcement procedures, including starting with a higher rate non-monetary reinforcement schedule and minimizing the salience of other types of reinforcers such as financial incentives and staff contact. The optimal reinforcement schedule in this setting should be investigated in future research. Fourth, the current findings may reflect self-selection bias, as those who enrolled and remained in the study may be intrinsically motivated, hence view the non-monetary rewards as less valuable than anticipated. Finally, it is possible that the inspirational quotes increased engagement by boosting positive affect and cognitive processing, and/or by serving as a reminder to self-report, as opposed to reciprocity. Future studies should investigate the mechanisms underlying the effect of such operationalization of reciprocity. Future studies should also consider developmental differences in adolescents and emerging adults, as well as seasonal variations in substance use among youth.

Conclusion

Consistent with *Stage I* of the NIH Stage Model (Onken et al., 2014) and the *preparation* phase of MOST (Collins, 2018), this study serves as an early check on the translation of selected engagement strategies to a particular mHealth setting. Although proof-of-concept studies are not used to finalize decisions about which component should be included in optimized interventions, they can be used to pre-screen components if the results indicate that a certain component is not ready for consideration (Collins, 2018). The results of the current study provide initial support for the translation of the reciprocity strategy into the SARA mHealth setting. However, the translation of non-monetary reinforcement requires further consideration prior to inclusion in a full scale MRT, as it may lead to different outcomes when operationalized in various ways. These results highlight the importance of conducting proof-of-concept studies to optimize the translation of engagement strategies into mHealth settings prior to conducting full scale trials.

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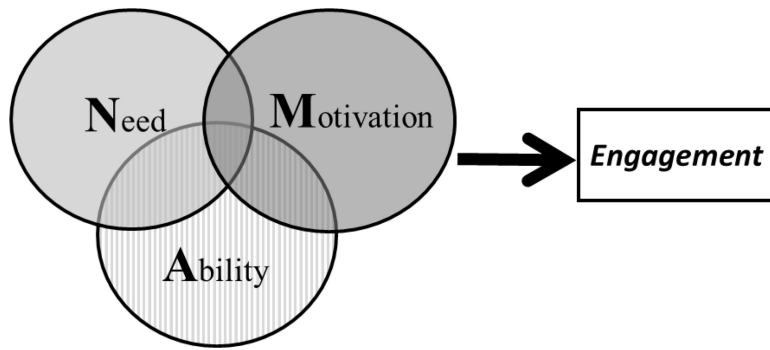


Figure 1.
The Need, Ability & Motivation (NAM) logic model

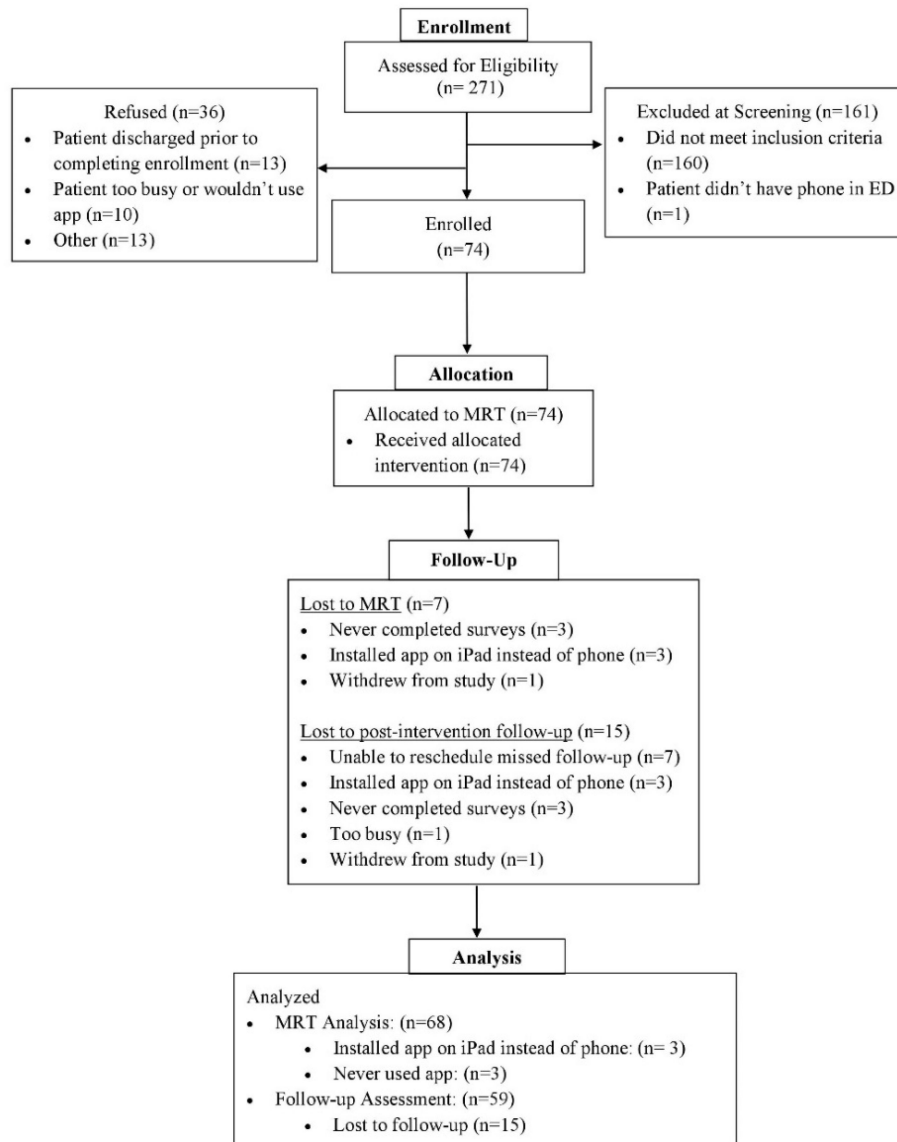


Figure 2.
MRT Consort Diagram for Study Enrollment

Table 1:

Main Effect Analyses

| Main effect analyses ¹ | Reciprocity Strategy (N= 68) | | | Non-Monetary Reinforcer | | | | | |
|--|---------------------------------|-------------------------------|--|---|-------------------------------|--|---|-------------------------------|--|
| | | | | Entertaining Content (N= 50) | | | Personalized Information (N=50) | | |
| | Beta (Imputed ²) | SE (Imputed ²) | Exp (beta) (Imputed ²) | Beta (Imputed ²) | SE (Imputed ²) | Exp (beta) (Imputed ²) | Beta (Imputed ²) | SE (Imputed ²) | Exp (beta) (Imputed ²) |
| Causal effect ³ (engagement strategy=yes) | .05 (.05) | .04 (.04) | 1.05 [1.97, 1.13] (1.05) [.97, 1.13] | -.04 (-.04) | .04 (.03) | .96 [.88, 1.04] (.97) [.91, 1.03] | -.02 (-.02) | .04 (.04) | .98 [.90, 1.06] (.98) [.90, 1.06] |
| Control Variables ⁴ | | | | | | | | | |
| App usage outside of self-reporting (yes=1) | .63** (.48**) | .17 (.18) | 1.89 [1.26, 2.52] (1.61) [1.04, 2.18] | .13 (.10) | .10 (.08) | 1.13 [.91, 1.35] (1.11) [.94, 1.28] | .01 (-.01) | .08 (.06) | 1.01 [.85, 1.17] (1.00) [.88, 1.12] |
| Prior day self-reporting (yes=1) | .42** (.49**) | .11 (.13) | 1.52 [1.19, 1.85] (1.64) [1.22, 2.06] | .25** (.24**) | .07 (.07) | 1.28 [1.10, 1.46] (1.27) [1.10, 1.44] | .22** (.24**) | .08 (.07) | 1.25 [1.05, 1.45] (1.28) [1.10, 1.46] |
| Prior contact by study staff (yes=1) | -.17** (-.18**) | .04 (.04) | .84 [1.77, .91] (.83) [.76, .90] | -.08 [†] (-.07 [†]) | .04 (.04) | .92 [.85, .99] (.93) [.86, 1.00] | -.09 [†] (-.09 [†]) | .05 (.05) | .91 [.82, 1.00] (.91) [.82, 1.00] |

[†] $p < 0.10$
^{*} $p < 0.05$
^{**} $p < 0.01$

95% Confidence Intervals are provided in the square brackets—[lower bound, upper bound].

¹ Both hypotheses as well as control variables are pre-specified (see open science protocol in Rabbi et al., 2017).

² Imputed =summary based on 10 imputed datasets

³ For reciprocity strategy, the term 'effect' refers to 4pm prompt relative to no 4pm prompt; for the non-monetary reinforcers 'effect' refers to offering a reinforcer relative to no reinforcer following survey (for entertaining content) or active tasks (for personalized information) completion.

⁴ Although estimates pertaining to the control variables are provided for completeness, we caution readers against interpreting them since correct specification of this part of the model is not required to yield consistent estimates of the causal effect of the randomized engagement strategies (see Boruvka et al., 2016).

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Table 2:

Summary of Moderation Analyses

| Moderation Analyses ³ | | Reciprocity Strategy (N= 68 participants, D= 1954 days) | | | | Non-Monetary Reinforcer | | | | |
|--|---|---|----------------------------|------------------------------------|------------------------------|----------------------------|------------------------------------|------------------------------|----------------------------|------------------------------------|
| | | Beta (Imputed ^f) | SE (Imputed ^f) | Exp (beta) (Imputed ^f) | Beta (Imputed ^f) | SE (Imputed ^f) | Exp (beta) (Imputed ^f) | Beta (Imputed ^f) | SE (Imputed ^f) | Exp (beta) (Imputed ^f) |
| Moderator: Weekend (=1) vs. weekdays (=0) | Effect ² on week days | .01 (.00) | .05 (.05) | 1.01 (1.00) | -.03 (-.03) | .05 (.05) | 0.97 (.97) | .01 (.01) | .05 (.05) | 1.01 (1.01) |
| | Effect ² on weekend days | .17* (.16*) | .07 (.07) | 1.18 (1.18) | -.04 (-.04) | .06 (.07) | .96 (.96) | -.12 (-.12) | .08 (.08) | .89 (.89) |
| | Interaction | .16* (.16*) | .08 (.08) | 1.17 (1.17) | -.01 (-.01) | .09 (.09) | .99 (.99) | -.13 (-.12) | .10 (.10) | .88 (.89) |
| Moderator: Prior contact by study staff (yes=1; no=0) | Effect ² when prior contact =no | .02 (.02) | .05 (.05) | 1.02 (1.02) | -.03 (-.03) | .05 (.05) | .97 (.97) | -.10* (-.09 [†]) | .05 (.05) | .91 (.92) |
| | Effect ² when prior contact =yes | .10 (.10) | .07 (.07) | 1.11 (1.10) | -.05 (-.04) | .06 (.06) | .95 (.96) | .10 (.10) | .08 (.08) | 1.10 (1.10) |
| Moderator: Prior app usage for other reasons (yes=1; no=0) | Interaction | .08 (.08) | .07 (.08) | 1.09 (1.08) | -.02 (-.02) | .08 (.08) | .98 (.99) | .20* (.19*) | .09 (.09) | 1.22 (1.20) |
| | Effect ² when app usage =no | .30 [†] (.19) | .16 (.16) | 1.35 (1.21) | -.06 (-.06) | .14 (.13) | .94 (.94) | -.14 (-.09) | .13 (.11) | .87 (.92) |
| | Effect ² when app usage =yes | .02 (.02) | .04 (.04) | 1.02 (1.02) | -.03 (-.03) | .04 (.04) | .97 (.97) | -.02 (-.02) | .04 (.04) | .98 (.98) |
| Moderator: Prior day self-reporting (yes=1; no=0) | Interaction | -.27 [†] (-.17) | .16 (.16) | .76 (.85) | .03 (.03) | .15 (.14) | 1.03 (1.03) | .12 (.07) | .14 (.12) | 1.13 (1.07) |
| | Effect ² when prior day self-report =no | .15 (.13) | .11 (.12) | 1.16 (1.13) | -.29* (-.28*) | .13 (.13) | .75 (.76) | .31* (.28*) | .13 (.13) | 1.36 (1.32) |
| | Effect ² when prior day self-report =yes | .03 (.02) | .04 (.04) | 1.03 (1.03) | .01 (.01) | .04 (.04) | 1.01 (1.01) | -.10* (-.09 [†]) | .05 (.04) | .91 (.92) |

| Moderation Analyses ³ | Non-Monetary Reinforcer | | | | | | | | | | | |
|----------------------------------|---|----------------------------|------------------------------------|------------------------------|---|------------------------------------|------------------------------|----------------------------|---|----------------------------|------------------------------------|--|
| | Reciprocity Strategy (N= 68 participants, D= 1954 days) | | | | Entertaining Content (N= 50 participants, D= 1400 days) | | | | Personalized Information (N= 50 participants, D= 1300 days) | | | |
| | Beta (Imputed ¹) | SE (Imputed ¹) | Exp (beta) (Imputed ¹) | Beta (Imputed ¹) | SE (Imputed ¹) | Exp (beta) (Imputed ¹) | Beta (Imputed ¹) | SE (Imputed ¹) | Beta (Imputed ¹) | SE (Imputed ¹) | Exp (beta) (Imputed ¹) | |
| Interaction | -.12 (-.10) | .11 (.11) | .89 (.91) | .31* (.29*) | .13 (.13) | 1.36 (1.34) | -.40** (-.36**) | .14 (.13) | | | .67 (.67) | |

¹ $p < 0.10$

* $p < 0.05$

** $p < 0.01$

¹ Imputed =summary based on 10 imputed datasets

² For reciprocity strategy, the term 'effect' refers to 4pm prompt relative to no 4pm prompt; for the non-monetary reinforcers 'effect' refers to offering a reinforcer relative to no reinforcer following survey (for entertaining content) or active tasks (for personalized information) completion.

³ Moderation analyses include the same control covariates as in main effect analysis; for brevity we did not include information concerning their estimated parameters in the table.