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Sensitivity to financial rewards and impression management links to smartphone use and dependence

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Abstract

Computational modeling and brain imaging studies suggest that sensitivity to rewards and behaviorist learning principles partly explain smartphone engagement patterns and potentially smartphone dependence. Responses to a questionnaire, and observational measures of smartphone use were recorded for 121 university students. Each participant was also tested with a laboratory task of reward sensitivity and a test of verbal operant conditioning. Twenty-three percent of the sample had probable smartphone addiction. Using multivariate regression, smartphone use, particularly the number of instant messenger services employed, was shown to be significantly and independently predicted by reward sensitivity (a positive relationship), and by instrumental conditioning (a negative relationship). However, the latter association was driven by a subset of participants who developed declarative knowledge of the response-reinforcer contingency. This suggests a process of impression management driven by experimental demand characteristics, producing goal-directed instrumental behavior not habit-based learning. No other measures of smartphone use, including the self-report scale, were significantly associated with the experimental tasks. We conclude that stronger engagement with smartphones, in particular instant messenger services, may be linked to people being more sensitive to rewarding stimuli, suggestive of a motivational or learning mechanism. We propose that this mechanism could underly problem smartphone use and dependence. It also potentially explains why some aspects of smartphone use, such as habitual actions, appear to be poorly measured by technology-use questionnaires. A serendipitous secondary finding confirmed that smartphone use reflected active self-presentation. Our 'conditioning' task-induced this behavior in the laboratory and could be used in social-cognition experimental studies.

Keywords: *smartphone, reward processing, internet addiction, impression management, instrumental conditioning*

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The emergence of the internet in the late 20th century led to profound changes in the way many people live their lives. Many of these changes are generally seen in a positive light, particularly the enhanced communication opportunities provided by email, and more recently, videocalls and instant messenger services. Most recently, the rapid uptake of smartphones, essentially handheld personal computers that are always connected to the internet, has undoubtedly increased the impact of internet access on individuals. Many people find this constant connectivity very rewarding (Genner, 2017). University students, for example, consistently report very high levels of smartphone interaction, typically over six hours per day: over one-third of their time spent awake (Alosaimi, Alyahya, Alshahwan, Al Mahyijari, & Shaik, 2016; Kim, Kim, & Jee, 2015; Volungis, Kalpidou, Popores, & Joyce, 2019). This time is mainly focused on social communication, such as instant messaging and social media (Vorderer, Krömer, & Schneider, 2016). Furthermore, as the devices are typically operated as always-turned-on, in addition to disrupted sleep, many people are now exposed to potentially rewarding social stimuli over the full 24-hour daily cycle (Rod, Dissing, Clark, Gerds, & Lund, 2018).

Reward sensitivity

Rewards are things that, from a psychological perspective, induce feelings of pleasure, and from a biosciences and behaviorist perspective, positively reinforce learned behavior, or act as goals (Schultz, 2000). Positive social interactions between people appear to influence learning in the same way as natural rewards (Jones et al., 2011), and can thus be potent reinforcers of instrumental behavior. People frequently use smartphone devices to present themselves in a positive light, such as by posting travel photographs and video clips (Lin, Younbo, & Sim, 2015; Lyu, 2016). One consequence of this is that posts to many current social media platforms (e.g., Facebook, Instagram, or Twitter) then attract likes and comments. The continuous availability, and action of interacting with a smartphone with frequent socially rewarding experiences, may potentially be habit-forming. Evidence suggests that people who use their smartphones for social purposes are most likely to develop habitual use (Van Deursen, Bolle, Hegner, & Kommers, 2015). Furthermore, behaviors such as checking messenger services and social media, like any other behaviors followed by reward, can become instrumentally conditioned, potentially leading to addiction (Foddy, 2016). It is particularly notable that the potentially rewarding stimuli arrive unpredictably with many aspects of internet interaction, essentially on a variable ratio reinforcement schedule (Cash, Rae, Steel, & Winkler, 2012). Such schedules are particularly potent modifiers of behavior and may underlie addictive behaviors, such as compulsive gambling (Skinner, 1963).

Software designers involved in smartphone app development, have reported their concerns that features such as likes, the red dots on icons that indicate new information, and the pull-to-refresh feature, amongst others, are deliberately included to condition repetitive behavior (Lewis, 2017). This is most evident in response to ‘likes’ on social media. Research on how these may have reward value has mainly come from functional brain imaging, rather than behavioral sciences.

The area of the brain most closely linked to reward signals in general (Knutson, Adams, Fong, & Hommer, 2001) and to the effects of addictive substances (Koob & Volkow, 2010), is the nucleus accumbens, part of the limbic system. This area has been found to be activated when people look at images that have received many likes on Instagram. In one study, samples of adolescents and young adults (college students) were asked to provide photos from their own Instagram accounts. When the participants viewed the photos during functional Magnetic Resonance Imaging (MRI) of the brain they had larger activations in their nuclei accumbens for photos that had received many likes, compared to those that had received few likes (Sherman, Greenfield, Hernandez, & Dapretto, 2018). In a different functional MRI study, young adults viewed photos of either themselves or a stranger, and for each photo they were also given a character evaluation that they were told came from a panel of judges. Receiving positive character evaluations to their own photos, compared to for the stranger, was associated with nucleus accumbens activity, and the extent of the activity was correlated with how much the individuals engage with Facebook (Meshi, Morawetz, & Heekeren, 2013). Also, smaller volumes of this brain area have been linked to high Facebook use (Montag et al., 2017), high social media use in general (He, Turel, Brevers, & Bechara, 2017), and high use of smartphone messenger services (Montag et al., 2018).

Although seemingly paradoxical, smaller nuclei accumbens may be a biomarker for reward sensitivity. In a sample of 233 male adult participants who underwent structural MRI, volumes of the left nucleus accumbens were found to negatively correlate with reward sensitivity scores (Adrian-Ventura, Costumero, Parcet, & Avila, 2019) as measured with the Sensitivity to Punishment and Sensitivity to Reward Questionnaire (Torrubia, Ávila, Moltó, & Caseras, 2001). Smaller volumes of the nuclei accumbens are also linked to a greater risk of developing substance dependence (Urosevic et al., 2015). This all suggests that variation in sensitivity to rewards could be a substantial feature of smartphone use.

Behavioral research on smartphone use and reward sensitivity is somewhat lagging behind neuroscientific research. Several researchers have theorized that reinforcement-based learning may underlie compulsive or addictive use of internet technology (LaRose, Lin, & Eastin, 2003; Meerkerk, van den Eijnden, Franken, & Garretsen, 2010; Putnam, 2000), but without providing evidence. A computational modeling study of a large corpus of actual online behavior, recently available as a preprint, has suggested that patterns of social media use are consistent with models of reinforcement learning used to explain the performance of animals in behaviorist studies (Lindström, Bellander, Chang, Tobler, & Amodio, 2019). Consequently, there is a wealth of theory and circumstantial associations implying that some aspects of smartphone use are habitual, and partly driven by how sensitive people are to rewarding stimuli, but little evidence.

Susceptibility to instrumental conditioning

We can easily see how behaviors such as checking one's smartphone and noticing a 'like' or a message from a friend could be rewarding and thus reinforce the checking behavior, leading to habitual repetition. Accordingly, Meerkerk et al. (2010; p. 729) have suggested that "*...the internet can be seen as a giant web of individually tailored Skinner boxes where the behavior of its users is reinforced through classical and operant conditioning mechanisms.*" By this, the authors are arguing that many aspects of internet use in general provide intermittent positive reinforcements, which as suggested above, appear to conform to variable ratio reinforcement schedules. This applies to smartphones, for which the internet is fully accessible. However, smartphone use is particularly linked to social media and instant messenger use (Vorderer et al., 2016). This social aspect is important because people, as social beings, respond to social cues in the same ways as to natural rewards which drive reinforcement learning (Jones et al., 2011).

In theory then, behaviors involving smartphones which are followed by rewards, such as 'likes' or receiving instant messages from friends, could become 'stamped in,' in the language of instrumental conditioning proposed by Thorndike (1911), and later developed as operant conditioning by Skinner (e.g., Skinner, 1963). This is learning that is said by behaviorists to be both unconscious and automatic (Brewer, 1974). In modern terminology, this form of instrumental conditioning leads to habit learning, as opposed to conscious, intentional goal-directed learning, which is also now recognized as a form of instrumental conditioning (O'Doherty, Cockburn, & Pauli, 2017; Yin & Knowlton, 2006). In the language of cognitive psychology, habit learning produces procedural (or implicit) memory, and goal-directed control stems from declarative (or explicit) memory (Dayan, 2009). Thus, a defining feature of habit-based instrumental conditioning is that it is not accessible to verbal report. This distinction is important because people process information differently when contingencies are consciously noticed, altering their behavior (Costea, Jurchiş, & Opre, 2016). Relevant here is a point raised by Ellis, Davidson, Shaw, and Geyer (2019), that habitual behavior, such as smartphone checking, may be poorly measured by self-report questionnaires, and that a psychological understanding of sustained technology use may be better achieved by considering both conscious, declarative, decisions to use devices and habitual responses (Shaw, Ellis, & Ziegler, 2018).

Current study

In this study, we aimed to examine whether individual differences in sensitivity to actual rewards (financial incentives given during a psychomotor task) and susceptibility to an instrumental conditioning procedure (in which trial-by-trial praise was given for selected responses as a potential social reinforcer) associate with indices of smartphone use in a large sample of university students. The indices of smartphone use were self-report phone use on a questionnaire, observation of smartphone use when in the laboratory, and recent use of apps, gleaned from the battery meters of participants' phones. We were particularly interested in whether potentially compulsive behaviors, such as keeping the phone in one's hand, extensive use of social media, and instant messenger services, would be associated with measures of reward sensitivity and conditionability. Thus, we hypothesized that observational measures of smartphone use would be correlated with measures of our laboratory-based measures of reward sensitivity and conditioning. A second hypothesis was that learning, if observed, will be habitual. The third hypothesis was that actual behavioral observations of phone-use would be more strongly associated, compared to a questionnaire on phone use, with laboratory-based measures of learning and reward sensitivity.

METHOD

Participants

One hundred and twenty-one undergraduate students were recruited at a university in Ecuador. These were studying for a range of majors, but the most common were psychology (n = 46), business administration (n = 19) and engineering (n = 17). The sample size of 121 was chosen somewhat opportunistically as it could be achieved by unpaid research assistants, while surpassing the number needed for medium-sized correlations (Gignac & Szodorai, 2016), if present, to reach statistical significance at a .05 threshold (two-tailed). The mean age of the sample was 21.9 (SD = 1.8, range 18-27) and 70 (58%) self-identified as female. All were speakers of Castilian Spanish.

Assessments

Smartphone use behavior. Our self-report assessment was the Mobile Phone Problem Use Scale (MPPUS; Bianchi & Phillips, 2005), in a validated Spanish-language version (Olatz, Luisa, & Montserrat, 2012). This is a 27-item questionnaire of phone-related behaviors which potentially cause difficulties for users. It has high internal consistency with a Cronbach's α of .97 (Olatz et al., 2012). To contrast with that, we also recorded observational measures of smartphone use. The researchers recorded (yes/no) whether the participant had a smartphone in their hands when they came into the interview room (henceforth referred to as the phone-in-hand variable). Researchers also recorded how many times the participants checked their phones during the consent procedure and the initial collection of demographic information (approximately 10 minutes), referred to as the phone-checking variable.

Researchers also examined the battery meter of each smartphone and recorded any social network applications and messenger service applications that had been recently used. The battery meter on all of the smartphones commonly used at the time of data collection provides details of which apps have been used since the last time the battery was fully charged. We recorded the number of minutes spent on each app, if available. In some systems the information was only given as a percentage of battery used, or megabytes of information, which was recorded instead. As these were on different scales, at the data curation stage, we counted the number of instant messaging services that had been used recently, including Facebook Messenger, Snapchat, and WhatsApp, and the number of social media services that had been used, including Facebook, Instagram, and Twitter. These are referred to henceforth as the messenger-services variable and the social-media variable.

Reward processing. Reward sensitivity was measured with the Card Arranging Reward Responsivity Objective Test (CARROT; Powell, Dawkins, & Davis, 2002; Powell, al-Adawi, Morgan, & Greenwood, 1996), a psychomotor card sorting task. This task has previously been used extensively to measure reward sensitivity in relation to dopamine psychopharmacology (e.g., Powell et al., 1996) and addiction (e.g., al-Adawi & Powell, 1997; Dawkins, Powell, West, Powell, & Pickering, 2006; Kambouropoulos & Staiger, 2001; Powell et al., 2002). Participants are given a stack of cards and are asked to read the five-digit string on each card and sort as many as possible, within a time limit, into categories based on the string containing a '1', a '2' or a '3'. On one trial, participants receive a reward of a US$ 25-cent coin for every five cards sorted. There are also two unrewarded trials performed, one before and one after the rewarded trial. The crucial variable is the change in the number of cards sorted with rewards compared to the average of the two trials performed without rewards. Relatively large increases in the number of cards sorted under the reward condition are taken as a measure of reward sensitivity. Reliability has been demonstrated by stability of scores over separate testing sessions and the validity as a measure of reward sensitivity by an average increase in response times under reward of 4% (Powell et al., 1996).

Instrumental conditioning. To measure the extent to which participants can be conditioned, we produced an experimental task based on Taffel's verbal operant conditioning procedure (Taffel, 1955). In this task, participants are presented with a verb and a choice of pronouns, and they are required to say sentences containing them. The experimenter says 'good' whenever the participant uses a first-person construction. In our version, for use in Ecuador, we used the Spanish present perfect tense. There were four practice trials before the 80 test trials. In each trial a past participle verb form was presented in the center of a computer screen (e.g., *'cocinado'* meaning cooked, or *'escrito'* meaning written), with choices from four different forms of the auxiliary verb *'haber'*; one in each corner of the screen. The verb forms of 'haber' are equivalent to the English, 'I have', 'you have' etc. The first 30 trials had no reinforcement, the other 50 did. This was in the form of the experimenter saying '*muy bien'* (meaning 'very good' in English) whenever the participant selected a first-person auxiliary verb form (equivalent to 'I have' and 'we have'). A schematic representation of the stimuli used is shown in Figure 1. To derive a measure of instrumental conditionability we took the change in use of first-person responses from the first 30 trials to the last 30 trials; if participants are influenced by the experimental manipulation (the reinforcement) they will show a change in frequency of the reinforced constructions.

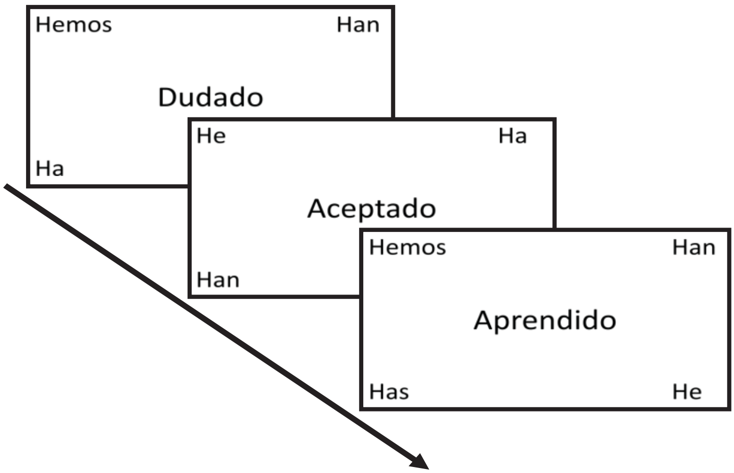

Figure 1. Sample stimuli for successive trials in the Operant Task. *Note:* The participant says a sentence aloud for each of 80 screens displayed (i.e. a single trial). For example, one could say *'hemos aprendido sobre la desnutrición'* (we have learnt about malnutrition). During the last 50 trials, the experimenter says *'muy bien'* (very good) whenever the participant chooses a first-person construction. The axillary verbs in the corners change place on each trial, and a different main verb is used in the central position in each trial

Immediately after completing the 80 trials of the Operant Task, the participants were asked "did my behavior during the task influence your choices of words in any way"? and "I was saying *'muy bien'* after some words: Which words was I saying that after"? Responses were scored as identification on none, one, or both reinforced words.

Procedure

All participants were interviewed in one-to-one sessions in a private room at the same university. Written informed consent was taken from each participant, followed by a collection of demographic information. During that phase, the researcher also recorded observational data on the participants' use of their smartphones. The participants were then asked to put their smartphones away in their bags. All participants then completed the Operant Task and then the CARROT. This took about 20 minutes. The sequence of these two tests was not counterbalanced. A further battery of cognitive tests was administered (not reported here), and the self-report phone scale, the MPPUS. All participants were debriefed and reimbursed for their participation with a payment of US$10 plus however much they earned in rewards on the CARROT (range US$ 2.50 - 4.75). In total, the session took about 80 minutes per participant. The full data for the whole interview for each participant is available in a public repository at http://dx.doi.org/10.23668/psycharchives.2791.

The research protocol was approved by a recognized research ethics committee. Furthermore, the research was compliant with ethical standards as set out by the American Psychological Association and the Declaration of Helsinki, as well as with national and international laws.

RESULTS

Descriptive statistics and psychometric properties of the assessments

The mean score for the MPPUS was 102.97 (SD = 40.87). A previously defined cut-off score for problematic use has been given as MPPUS scores > 138, being the 95th percentile in a Spanish normative sample (de-Sola et al., 2017). de-Sola et al. (2017) suggested that scores in that range indicate smartphone addiction. In the current sample, 28 out of the 121 participants (23%) met that criterion. Scores on the MPPUS were normally distributed, based on published norms for skew and kurtosis (Kim, 2013). The scale also had a *'good'* to *'excellent'* level of internal consistency, Cronbach's α = .90. We had the opportunity to include the MPPUS in a four-week test-retest study reported previously (Pluck et al., 2020). This comprised a mixed sample of 21 students and university employees, mean age 28.65 (SD = 9.75), 13/21 (62%) female and for the MPPUS there was good test-retest reliability (r = .81, p < .001).

Next, we considered the observational measures of smartphone use. Of the 121 participants, 119 (98%) arrived at the research interview with a smartphone, even though there was no information given to them to bring one, or that the research was about smartphone use. The two who did not bring smartphones nevertheless were smartphone owners and returned to the laboratory at a later date, so that the applications-used information could be obtained. Observational smartphone data was accidentally not collected for one participant. Of the 120 participants for whom data was recorded, 47 (39%) arrived at the test session with a smartphone in hand. During the consent procedure and collection of demographic data, 40/120 (33%) participants checked their phone. The mean number of checks for all 120 participants were data was recorded was 0.58 (SD = 1.06, range = 0 - 6, median = 0). In fact, these two variables, phone-in-hand and phone-checking, largely overlapped. Of the 40 participants who checked their phones more than once, all were members of the subgroup of 47 participants who arrived with a phone in hand. Social-media and messenger-services variables both had normal distributions, based on kurtosis and skew. However, for the number of times the person checked their phone, scores for both skew (z = 11.02) and kurtosis (z = 15.63) deviated substantially and significantly from normal, based on standardized interpretation of the z scores (Kim, 2013).

To gain an idea of the validity of the different measures of smartphone use we examined the correlations between them. These are shown in Table 1. The observational phone-in-hand and phone-checking variables were very highly correlated, to the extent that they represent redundant measures. Consequently, only the phone-in-hand variable is included in later analyses. In contrast, the messenger-services and social-media variables significantly correlated, and the latter of these was also correlated with MPPUS scores. The size of these correlation r values between MPPUS scores and social-media and messenger service variables, .14 and .24 respectively, are similar to previously reported correlations between objective measures and several different self-report scales of smartphone use, which was mean r = .21 (Ellis et al., 2019). Further, although they may seem somewhat low, they correspond to 'small' and 'medium' effect sizes for research in social sciences (Gignac & Szodorai, 2016).

Table 1
Zero-order Correlations Between the Different Measures of Smartphone Use

	1. MPPUS	2. Social-media	3. Messenger-services	4. Phone-in-hand [a]	5. Phone-checking [b]
1.		.24 **	.14	.07	.07
2.			.34 ***	.04	.03
3.				.05	.05
4.					.86 ***

[a]Point-biserial correlation, all other coefficients are Pearson's r values except [b]Spearman's RHO, ** $p < .01$, *** $p < .001$

The CARROT contains only three data-contributing trials and Cronbach's α is not useful, however, all three trials were intercorrelated, with r values ranging from .64 to .84, suggesting they measured similar constructs. In the rewarded condition, the participants sorted a mean of 74.49 (SD = 9.52) cards, compared to a mean of 71.77 (SD = 7.65) cards in the non-rewarded conditions, a significant difference, Wilcoxon Signed Rank Test = 5.36, $p < .001$. This 4% increase in sorting speed in response to financial incentives suggests that the procedure is a valid measure of reward sensitivity, and is equal to the 4% response augmentation reported by the test developers (Powell et al., 1996). For the Operant Task, in the 30 unreinforced trials, participants selected a mean of 15.35 (SD = 2.98) first-person forms, compared to 16.71 (SD = 4.39) in the reinforced condition, an increase of

9%, and a significant difference, Wilcoxon Signed Rank Test = 3.21, p = .001. This suggests that the procedure was sensitive to the effects of the reinforcer on behavior.

However, for both the CARROT and Operant Task performance measures, the data distributions differed significantly from normal, based on analysis of skew and kurtosis (Kim, 2013). For this reason, correlations involving those two variables were performed on rankit transformed data and analyzed with Pearson statistics, a procedure that gives the best control over type I errors (Bishara & Hittner, 2012). Between and within-group comparisons were conducted with non-parametric methods. Mann Whitney U tests and Wilcoxon Signed Rank tests were employed as these are the principal non-parametric alternatives to independent and paired-sample t-tests (Sheskin, 2020). For regression analyses, raw data was used, but the model residuals were checked for normal distributions.

Table 2
Zero Correlations Between Primary Measures and Demographic Variables

	Age	Gender[a]
MPPUS	-.18*	.15
Social-media	.00	.16
Messenger-services	-.11	.14
Phone-in-hand	-.02	.10
CARROT	.19*	-.04
Operant Task	.17	.03

[a]coded as 1 = male and 2 = female. * $p < .05$

Associations of reward sensitivity, conditioning, and smartphone use with demographic variables

The correlation matrix of smartphone use, reward sensitivity and conditionability measures with demographic variables are shown in Table 2. Age was significantly associated with MMPUS scores and with CARROT scores, and there were indications that female participants tended to score higher for the MPPUS, social-media and messenger-services variables, and were more likely to be positive on the phone-in-hand variable, although these did not reach statistical significance. Nevertheless, as there was a consistent pattern of qualitatively small correlations, both age and gender were used as covariates in later analyses in order to remove any extraneous variation due to age and gender.

Associations between smartphone use and reward sensitivity and instrumental conditioning

The phone-in-hand variable was associated with neither reward sensitivity, Mann-Whitney U = 1.45, p = .148, nor Operant Task scores Mann Whitney U = -0.68, p = .498.

Unlike the binary phone-in-hand variable, the other three measures of phone use, MPPUS, social-media, and messenger-services were continuous variables. As they were intercorrelated, we performed a multivariate linear regression. Although the intercorrelations may appear relatively low, they intercorrelated positively, with *r* values qualitatively ranging from ‘small’ to ‘large’ associations (Gignac & Szodorai, 2016). All three measures were entered together and used as a single dependent variable. The benefit of this approach is that it reduces the number of null-hypothesis tests. Instead of one for each dependent variable, there is just one for the combined dependent variable, reducing the type I error rate (Warne, 2014). CARROT scores and Operant Task scores were entered as covariates of interest. Age and gender were also added as covariates to be controlled for.

CARROT scores were found to be significantly associated with the combined dependent variable of smartphone use, $F(3, 107) = 354$, $p = .017$, $\eta_p^2 = .090$. Similarly, Operant Task scores were significantly associated with the combined dependent variable, $F(3, 107) = 2.94$, $p = .037$, $\eta_p^2 = .076$. The regression statistics for phone use variables predicting CARROT and Operant Task scores are shown in Table 3. The only significant associations were messenger-services with both CARROT and Operant Task scores. It should be noted that these were in opposite directions, a greater number of instant messenger apps was linked to more reward sensitivity on the CARROT, but lower scores on the Operant Task. It should also be noted that, as both were significant in the multivariate tests, they have independent associations with smartphone use. The model residuals had a distribution that did not differ significantly from normal.

Table 3
Regression Statistics Predicting Smartphone Use from CARROT and Operant Task Scores

		B	Standard error of *B*	*F*	Sig.	Observed power
CARROT	MPPUS	.291	.752	0.15	.699	.067
	Social-media	.004	.014	0.09	.765	.060
	Messenger-services	.041	.013	10.05	.002	.881
Operant Task	MPPUS	.642	.795	0.65	.421	.126
	Social-media	-.008	.015	0.28	.595	.083
	Messenger-services	-.039	.014	7.84	.006	.793

Habit-based or goal-directed conditioning?

The regression indicates a negative association between messenger service use and Operant Task performance, that is, those participants with the most messenger services tended to be the least susceptible to conditioning. After completion of the Operant Task, participants had been asked if they thought the researcher’s behavior had influenced them. Of the 121 participants, 64 (53%) responded positively.

However, only 28 were able to identify both words which were being reinforced, and a further 18 were able to identify one of the two reinforced words.

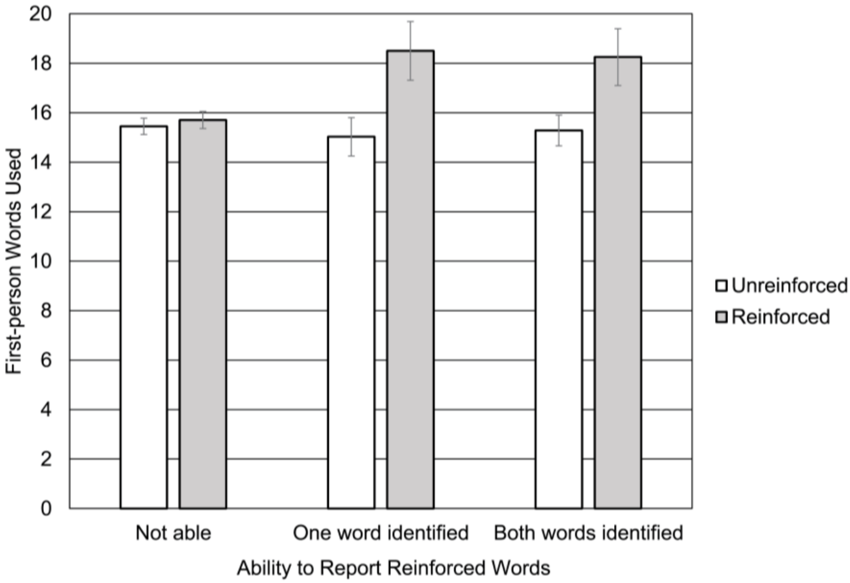

Figure 2. Mean (+SEM) of the number of first-person constructions in the Operant Task in the different groups based on their ability to report the response-reinforcement contingency

Figure 2 shows the mean number of first-person words selected, with and without reinforcement, in the groups based on their ability to verbally report what the reinforced words were after completing the task. Within-subject analyses (comparing unreinforced with reinforced performance) showed that there was no change in behavior in the 75 participants without awareness of the reinforced words, $F(1, 74) = .37$, $p = .543$, $\eta_p^2 = .005$. However, there was a change in behavior in the 18 participants who could identify one of the words, $F(1, 17) = 9.69$, $p = .006$, $\eta_p^2 = .363$, and the 28 participants who could identify both words, $F(1, 27) = 5.84$, $p = .023$, $\eta_p^2 = .18$. This shows that 'conditioning' only occurred in the presence of declarative knowledge of the response-reinforcement contingency, suggestive of goal-directed instrumental behavior.

We therefore calculated the correlations between smartphone use variables and Operant Task scores, dividing into groups based on those participants who could verbally report either one or both reinforced words ($n = 46$), or those with no awareness ($n = 75$). The only significant association between Operant Task scores and messenger-services used was in the group with awareness of the reinforced words, and this was a negative correlation, $r = -.34$, $p = .023$. Boxplots are used to show this relationship in Figure 3. For the group of participants without awareness of the reinforcer there was no evidence of a link between instrumental conditioning and number of messenger services used (r = -.13, p = .281) or any other smartphone variables.

It is notable from Figure 3, that on the Operant Task, many participants scored above zero, and others scored below zero, particularly those identified as using three different instant messenger services. A reduction in the use of first-person words, compared to the control condition, suggests that they actually reduced the frequency of the target responses when they were 'reinforced.' This further suggests deliberate goal-directed action, rather than habit formation. This issue will be explored in the Discussion.

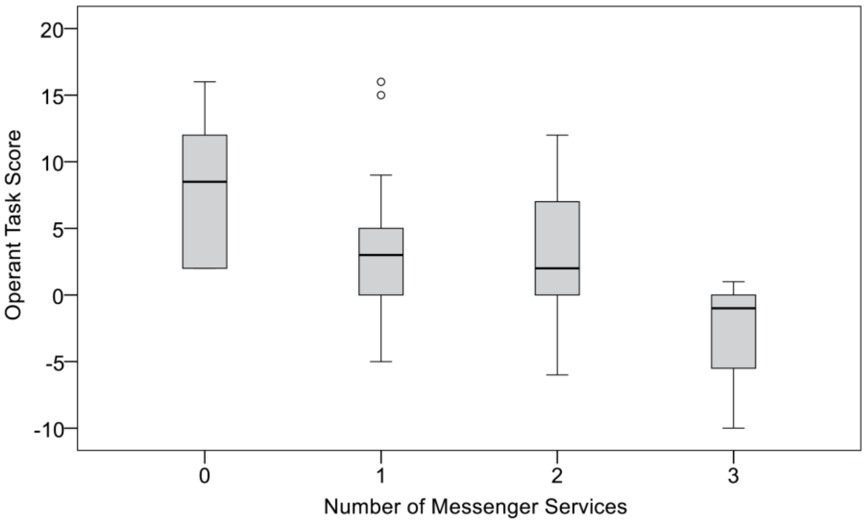

Figure 3. Boxplots showing the relationship between the use of smartphone messenger services and Operant Task scores for the participants with declarative knowledge of the response-reinforcement contingency (n = 46)

DISCUSSION

We investigated the potential associations of reward sensitivity and instrumental conditioning to smartphone use. We found that both were significantly associated with a combined variable of smartphone use, but particularly the number of instant messenger services used. We therefore, accept our hypothesis that smartphone use is related to reward sensitivity and instrumental conditioning.

Turning first to reward sensitivity, our data suggest that students who had recently used multiple instant messenger services showed greater sensitivity to monetary rewards in an established psychomotor task (the CARROT). This is consistent with brain imaging studies which have suggested enhanced rewardinduced neurophysiological responses in internet-addicted participants, compared to non-addicted participants (Dong, Huang, & Du, 2011; Wang et al., 2017). In particular, the use of smartphone messenger services has been associated with a reduced volume of the nuclei accumbens (Montag et al., 2018), which is often taken as a biomarker of enhanced reward sensitivity (Adrian-Ventura et al., 2019). Nevertheless, anatomical associations of internet use to reward sensitivity are essentially circumstantial. Here we provide behavioral evidence of a link.

This is consistent with some psychological studies that have reported reward sensitivity, measured as a self-report variable, being related to smartphone addiction (Kim et al., 2016). Though others have not found a link (Wilmer & Chein, 2016). Regardless, it has been argued that questionnaires of reward sensitivity lack the validity of behavioral tests which actually measure responses to rewards (Smillie, 2008). Furthermore, reward sensitivity, as a psychometric construct, has substantial conceptual overlap with personality measures of extraversion and impulsivity (Smillie, Pickering, & Jackson, 2006), and may not closely correspond to how people actually react to real-life rewards such as financial incentives or internet 'likes'. The current findings show that smartphone use, in particular instant messenger use, is related to actual behavioral sensitivity to rewards, providing convergent support to the existing self-report evidence.

The statistical association revealed in the regression analysis, that people with more instant messenger use are more behaviorally reactive to financial rewards, provides a possible explanation of why some people become more immersed in technologies, even to the point of addiction. They may have enhanced reward responses to the feedback provided by social media likes and interpersonal interaction via messenger services, and experiencing material as rewarding is an essential precursor to the development of addiction through instrumental conditioning (Foddy, 2016). We also point out that high reward sensitivity, as a personality trait, has frequently been associated with substance use disorders (Dawe & Loxton, 2004). Nearly a quarter of our sample (23%) could be considered to be addicted to their smartphones, based on a preestablished MPPUS cutoff score (de-Sola et al., 2017). Although, we should at this point state that despite many assertions about 'smartphone addiction' in the research literature, this is a controversial topic. Some argue that smartphone use may become problematic, but rarely would it meet the criteria for addiction, clinically defined (Panova, 2018).

It is noteworthy that reward sensitivity was statistically associated with an observational measure of smartphone use (messenger services observed in the battery meter), but not a self-report measure of phone use (MPPUS). This result is consistent with previous work suggesting that some aspects of smartphone use are more associated with automatic or habitual use, rather than active, attentive choices (Ellis et al., 2019; Shaw et al., 2018). This may be why reward sensitivity on an experimental task predicted the use of multiple instant messenger apps, but a self-report scale of phone use did not. We therefore also accept our hypothesis that smartphone behavior is more closely linked to laboratory-based reward sensitivity when measured observationally, than as responses on a self-report questionnaire.

The type of task that we used to measure instrumental conditioning is also often considered to measure sensitivity to reinforcement (Pickering & Gray, 2001). In addition, it is sometimes used as an alternative measure of reward sensitivity to the CARROT, as both are said to reveal increased sensitivity to rewards, for example, in people with bulimia nervosa (Dawe & Loxton, 2004). We could therefore anticipate that people with multiple messenger services would show more learning on our Operant Task, given that they are more reward sensitive. However, we found the opposite, implying that those with the heaviest messenger service use were the least conditionable.

One possible explanation for this negative relationship could be habituation to the reinforcer used (saying ‘very good’). It is known that such reinforcer habituation varies between individuals, with some people habituating much faster than others. For example, people with attention-deficit/hyperactivity disorder (ADHD) appear to rapidly habituate to reinforcers (Lloyd, Medina, Hawk, Fosco, & Richards, 2014). Notably, ADHD is also a strong risk factor for the development of smartphone addiction (Kim et al., 2019), suggesting that people with rapid reinforcer habituation would be overrepresented within groups with the highest smartphone usage. This may be part of the reason for the negative association reported here between instant messenger use and conditionability.

But this should be considered in the context of our finer-grained analyses of the data, which showed that ‘conditioning’ was only present in those participants who developed declarative knowledge of the response-reinforcer contingency. Many of the participants were aware of what the experimenter was attempting to do and modulated their behavior based on that knowledge. Consistent with this, some participants actually reduced the frequency of the reinforced behavior, compared to the baseline condition, even though they were able to verbally report the response-reinforcement contingency. A reduction in the ‘reinforced’ response in the presence of declarative knowledge of which responses were followed by rewards cannot be explained by traditional behaviorist principles, and in fact is consistent with it being deliberate goal-directed action. We therefore cannot accept our other hypothesis, that the Operant Task would produce habit-based learning.

The fact that some participants could report the response-reinforcement contingency, but did not demonstrate reinforcement of behavior, is very suggestive of the idea of the ‘apprehensive subject’. This says that participants in experiments actively alter their performance to present themselves in the best light (Kingsbury, Stevens, & Murray, 1975). When the response-reinforcer contingency is recognized, the apprehensive subject may try to confirm the experimenter’s aim by emitting the response, taking the ‘good subject’ role (e.g., to demonstrate their intelligence), or deliberately not emit it, taking the ‘negativistic subject’ role (e.g., to demonstrate their independence). Indeed, it has long been known that participants in experiments who report high levels of need for social approval are more susceptible to being ‘operantly conditioned’ (Marlowe, 1962) and that operant conditioning effects may be dependent on the perceived need for deference to the experimenter (Corr, 2004).

It appears that individuals who used multiple messenger services on their smartphones tended to take the ‘negativistic subject’ role. This may be because proneness to becoming easily angered is known to be a precursor of participants taking the negativistic role in experiments (Burns, Bruehl, & Caceres, 2004), and the problematic smartphone use is also linked with higher expressed anger (Elhai, Rozgonjuk, Yildirim, Alghraibeh, & Alafnan, 2019; Firat et al., 2018). More generally, it is clear that instant messenger use was linked to particular strategies of self-presentation, confirming previous research that impression management seems to be an important factor in social media (Lin et al., 2015; Lyu, 2016) and instant messenger service use (Grebelsky-Lichtman, Adato, & Traeger, 2020; Kobsa, Patil, & Meyer, 2012). The evidence presented, therefore, suggests that experimental demand characteristics best explain the observed association between messenger services and instrumental ‘conditionability’, as measured by our Operant Task. However, this is still a form of instrumental learning, one that is goal-directed (O'Doherty et al., 2017; Yin & Knowlton, 2006). This remains consistent with the multiple studies that have shown that the nucleus accumbens, part of the brain’s reward system, is linked to internet and messenger service use (He et al., 2017; Meshi et al., 2013; Montag et al., 2017; Montag et al., 2018; Sherman et al., 2018). This is because the nucleus accumbens is thought to be involved mainly in goal-directed learning, but not in habit learning (McDannald, Lucantonio, Burke, Niv, & Schoenbaum, 2011).

Nevertheless, a limitation of the current study is that we failed to measure susceptibility to habit-based instrumental conditioning directly. It may be that ‘conditioning’ tasks such as the Taffel procedure (Taffel, 1955), which we adapted and used, are actually better suited to the study of impression management and self-presentation. Although problematic for our research, this hints that operant conditioning ‘Taffel tasks’ may be a useful method to induce self-presentation behavior experimentally, which could be employed in social cognition research. A further limitation is that the Operant Task was administered before the CARROT for all participants, which might have increased the within-participant variance as an order effect (e.g., worse performance on the CARROT if fatigued after the Operant Task). On the other hand, by not counterbalancing the test order, we avoided additional extraneous between-participant variation, which would have introduced additional variance that could have a negative impact on the veracity of the between-participant regression statistics.

Further limitations of the current research should be addressed. Firstly, our observational measures of smartphone use, including whether the participant entered the lab holding a smartphone, and counts of social media and messenger apps in the battery meter may be rather crude. Secondly, the MPPUS, our self-report measure of smartphone use, was not validated specifically for use in

Ecuador. On the other hand, we did show that it appears to have good psychometric properties in the context we used it in, and that its lack of association with any experimental variables was not a consequence of poor reliability.

Conclusions. We failed to directly reveal an association of any smartphone-use variables with habit-based instrumental conditioning, due to experimental demand characteristics in our Operant Task, but this lead serendipitously to evidence that multiple instant messenger use is associated with personal impression management in a laboratory task. As much of the research on impression management uses questionaries, our result provides both confirmation of previous results highlighting the role of impression management in instant messenger engagement (Grebelsky-Lichtman et al., 2020; Kobsa et al., 2012), but also a way that experimental measures could be employed to study the phenomena in the psychology laboratory. We also found that self-reported phone use was not predicted by any of our experimental measures. However, we did show that the use of multiple messenger apps is predicted by individual differences in sensitivity to rewards, which despite the problems with our Operant Task, suggests a learning or motivational mechanism for that aspect of smartphone use. This may therefore be a feature of smartphone usage susceptible to compulsive use, and potentially to the development of dependency. Although some of the features of smartphones may have no negative health implications, the attention of psychiatrists and psychologists to instant messenger services and their reinforcing properties and potential for addiction is warranted.

Author note: The data that support the findings of this study are openly available in PsychArchives at http://dx.doi.org/10.23668/psycharchives.2791

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REFERENCES

Adrian-Ventura, J., Costumero, V., Parcet, M. A., & Avila, C. (2019). Linking personality and brain anatomy: A structural MRI approach to Reinforcement Sensitivity Theory. *Social Cognitive and Affective Neuroscience*, *14*(3), 329-338. http://dx.doi.org/10.1093/scan/nsz011

al-Adawi, S., & Powell, J. (1997). The influence of smoking on reward responsiveness and cognitive functions: A natural experiment. *Addiction*, *92*(12), 1773-1782. http://dx.doi.org/10.1111/j.1360-0443.1997.tb02897.x

Alosaimi, F. D., Alyahya, H., Alshahwan, H., Al Mahyijari, N., & Shaik, S. A. (2016). Smartphone addiction among university students in Riyadh, Saudi Arabia. *Saudi Medical Journal*, *37*(6), 675-683. http://dx.doi.org/10.15537/Smj.2016.6.14430

Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *Cyberpsychology and Behavior, 8*(1), 39-51. http://dx.doi.org/10.1089/cpb.2005.8.39

Bishara, A. J., & Hittner, J. B. (2012). Testing the significance of a correlation with nonnormal data: Comparison of Pearson, Spearman, transformation, and resampling approaches. *Psychological Methods, 17*(3), 399-417. http://dx.doi.org/10.1037/a0028087

Brewer, W. F. (1974). There is no convincing evidence for operant or classical conditioning in adult humans. In W. B. Weimer & D. S. Palermo (Eds.), *Cognition and the symbolic processes*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Burns, J. W., Bruehl, S., & Caceres, C. (2004). Anger management style, blood pressure reactivity, and acute pain sensitivity: Evidence for "Trait x Situation" models. *Annals of Behavioral Medicine*, *27*(3), 195-204. http://dx.doi.org/10.1207/s15324796abm2703_7

Cash, H. D., Rae, C., Steel, A., & Winkler, A. (2012). Internet addiction: A brief summary of research and practice. *Current Psychiatry Reviews*, *8*(4), 292-298. http://dx.doi.org/10.2174/157340012803520513

Corr, P. J. (2004). Reinforcement sensitivity theory and personality. *Neuroscience and Biobehavioral Reviews, 28*(3), 317-332. http://dx.doi.org/10.1016/j.neubiorev.2004.01.005

Costea, A. R., Jurchiş, R., & Opre, A. N. (2016). Influencing the expression of implicitly learned knowledge with subliminal priming. *Cognition, Brain, Behavior. An Interdisciplinary Journal*, *20*, 331-343.

Dawe, S., & Loxton, N. J. (2004). The role of impulsivity in the development of substance use and eating disorders. *Neuroscience and Biobehavioral Reviews, 28*(3), 343-351. http://dx.doi.org/10.1016/j.neubiorev.2004.03.007

Dawkins, L., Powell, J. H., West, R., Powell, J., & Pickering, A. (2006). A double-blind placebo controlled experimental study of nicotine: I- effects on incentive motivation. *Psychopharmacology (Berl), 189*(3), 355-367. http://dx.doi.org/10.1007/s00213-006-0588-8

Dayan, P. (2009). Goal-directed control and its antipodes. *Neural Networks, 22*(3), 213-219. http://dx.doi.org/10.1016/j.neunet.2009.03.004

de-Sola, J., Talledo, H., Rodríguez de Fonseca, F., & Rubio, G. (2017). Prevalence of problematic cell phone use in an adult population in Spain as assessed by the Mobile Phone Problem Use Scale (MPPUS). *PLoS One*, *12*(8), e0181184. http://dx.doi.org/10.1371/journal.pone.0181184

Dong, G., Huang, J., & Du, X. (2011). Enhanced reward sensitivity and decreased loss sensitivity in Internet addicts: An fMRI study during a guessing task. *Journal of Psychiatric Research, 45*(11), 1525-1529. http://dx.doi.org/10.1016/j.jpsychires.2011.06.017

Elhai, J. D., Rozgonjuk, D., Yildirim, C., Alghraibeh, A. M., & Alafnan, A. A. (2019). Worry and anger are associated with latent classes of problematic smartphone use severity among college students. *Journal of Affective Disorders, 246*, 209-216. http://dx.doi.org/10.1016/j.jad.2018.12.047

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. http://dx.doi.org/10.1016/j.ijhcs.2019.05.004

Firat, S., Gul, H., Sertcelik, M., Gul, A., Gurel, Y., & Kilic, B. G. (2018). The relationship between problematic smartphone use and psychiatric symptoms among adolescents who applied to psychiatry clinics. *Psychiatry Research, 270*, 97-103. http://dx.doi.org/10.1016/j.psychres.2018.09.015

Foddy, B. (2016). The pleasures and perils of operant behavior. In N. Heather & G. Segal (Eds.), *Addiction and choice: Rethinking the relationship*. Oxford, UK: Oxford University Press.

Genner, S. (2017). *On/off: Risks and rewards of the anytime-anywhere internet*. Zürich: vdf Hochschulverlag AG an der ETH.

Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences, 102*, 74-78. http://dx.doi.org/10.1016/j.paid.2016.06.069

Grebelsky-Lichtman, T., Adato, Z., & Traeger, S. (2020). Extending impression management theory: The need for privacy vs. the need to express information on instant messaging apps. *Studies in Media and Communication, 8*(1), 72-85. http://dx.doi.org/10.11114/smc.v8i1.4853

He, Q., Turel, O., Brevers, D., & Bechara, A. (2017). Excess social media use in normal populations is associated with amygdala-striatal but not with prefrontal morphology. *Psychiatry Research: Neuroimaging, 269*, 31-35. http://dx.doi.org/10.1016/j.pscychresns.2017.09.003

Jones, R. M., Somerville, L. H., Li, J., Ruberry, E. J., Libby, V., Glover, G., . . . Casey, B. J. (2011). Behavioral and neural properties of social reinforcement learning. *Journal of Neuroscience, 31*(37), 13039-13045. http://dx.doi.org/10.1523/JNEUROSCI.2972-11.2011

Kambouropoulos, N., & Staiger, P. K. (2001). The influence of sensitivity to reward on reactivity to alcohol-related cues. *Addiction, 96*(8), 1175-1185. http://dx.doi.org/10.1046/j.1360-0443.2001.968117510.x

Kim, H. Y. (2013). Statistical notes for clinical researchers: Assessing normal distribution (2) using skewness and kurtosis. *Restorative Dentistry and Endodontics, 38*(1), 52-54. http://dx.doi.org/10.5395/rde.2013.38.1.52

Kim, S. E., Kim, J. W., & Jee, Y. S. (2015). Relationship between smartphone addiction and physical activity in Chinese international students in Korea. *Journal of Behavioral Addictions, 4*(3), 200-205. http://dx.doi.org/10.1556/2006.4.2015.028

Kim, S. G., Park, J., Kim, H. T., Pan, Z., Lee, Y., & McIntyre, R. S. (2019). The relationship between smartphone addiction and symptoms of depression, anxiety, and attention-deficit/hyperactivity in South Korean adolescents. *Annals of General Psychiatry, 18*(1), 1-8. http://dx.doi.org/10.1186/s12991-019-0224-8

Kim, Y., Jeong, J. E., Cho, H., Jung, D. J., Kwak, M., Rho, M. J., . . . Choi, I. Y. (2016). Personality factors predicting smartphone addiction predisposition: Behavioral inhibition and activation systems, impulsivity, and self-control. *PLoS One, 11*(8), e0159788. http://dx.doi.org/10.1371/journal.pone.0159788

Kingsbury, S. J., Stevens, D. P., & Murray, E. J. (1975). Evaluation apprehension in verbal conditioning: A test of four subject effects models. *Journal of Personality and Social Psychology, 32*(2), 271-277. http://dx.doi.org/10.1037/0022-3514.32.2.271

Knutson, B., Adams, C. M., Fong, G. W., & Hommer, D. (2001). Anticipation of increasing monetary reward selectively recruits nucleus accumbens. *Journal of Neuroscience, 21*(16), RC159. http://dx.doi.org/10.1523/JNEUROSCI.21-16-j0002.2001

Kobsa, A., Patil, S., & Meyer, B. (2012). Privacy in instant messaging: An impression management model. *Behaviour and Information Technology, 31*(4), 355-370. http://dx.doi.org/10.1080/01449291003611326

Koob, G. F., & Volkow, N. D. (2010). Neurocircuitry of addiction. *Neuropsychopharmacology, 35*(1), 217-238. http://dx.doi.org/10.1038/npp.2009.110

LaRose, R., Lin, C. A., & Eastin, M. S. (2003). Unregulated Internet usage: Addiction, habit, or deficient self-regulation? *Media Psychology, 5*(3), 225-253. http://dx.doi.org/10.1207/S1532785XMEP0503_01

Lewis, P. (2017, October 6). 'Our minds can be hijacked': The tech insiders who fear a smartphone dystopia. *The Guardian Weekend Magazine*. https://www.theguardian.com/technology/2017/oct/05/smartphone-addiction-silicon-valley-dystopia

Lin, T. T., Younbo, J., & Sim, C. (2015). Towards an understanding of intention to use mobile videos: Impression management, perceived facilitation, and social norms. *Mobile Media and Communication, 3*(1), 106-124. http://dx.doi.org/10.1177/2050157914555426

Lindström, B., Bellander, M., Chang, A., Tobler, P. N., & Amodio, D. (2019, July 11). A computational reinforcement learning account of social media engagement. http://dx.doi.org/10.31234/osf.io/78mh5

Lloyd, D. R., Medina, D. J., Hawk, L. W., Fosco, W. D., & Richards, J. B. (2014). Habituation of reinforcer effectiveness. *Frontiers in Integrative Neuroscience, 7*, 107. http://dx.doi.org/10.3389/fnint.2013.00107

Lyu, S. O. (2016). Travel selfies on social media as objectified self-presentation. *Tourism Management, 54*, 185-195. http://dx.doi.org/10.1016/j.tourman.2015.11.001

Marlowe, D. (1962). Need for social approval and the operant conditioning of meaningful verbal behavior. *Journal of Consulting and Clinical Psychology, 26*, 79-83. http://dx.doi.org/10.1037/h0046129

McDannald, M. A., Lucantonio, F., Burke, K. A., Niv, Y., & Schoenbaum, G. (2011). Ventral striatum and orbitofrontal cortex are both required for model-based, but not model-free, reinforcement learning. *Journal of Neuroscience, 31*(7), 2700-2705. http://dx.doi.org/10.1523/JNEUROSCI.5499-10.2011

Meerkerk, G. J., van den Eijnden, R. J., Franken, I. H. A., & Garretsen, H. F. L. (2010). Is compulsive Internet use related to sensitivity to reward and punishment, and impulsivity? *Computers in Human Behavior, 26*(4), 729-735. http://dx.doi.org/10.1016/j.chb.2010.01.009

Meshi, D., Morawetz, C., & Heekeren, H. R. (2013). Nucleus accumbens response to gains in reputation for the self relative to gains for others predicts social media use. *Frontiers in Human Neuroscience, 7*, 439. http://dx.doi.org/10.3389/fnhum.2013.00439

Montag, C., Markowetz, A., Blaszkiewicz, K., Andone, I., Lachmann, B., Sariyska, R., . . . Markett, S. (2017). Facebook usage on smartphones and gray matter volume of the nucleus accumbens. *Behavioural Brain Research, 329*, 221-228. http://dx.doi.org/10.1016/j.bbr.2017.04.035

Montag, C., Zhao, Z., Sindermann, C., Xu, L., Fu, M., Li, J., . . . Becker, B. (2018). Internet communication disorder and the structure of the human brain: Initial insights on WeChat addiction. *Scientific Reports, 8*(1), 2155. http://dx.doi.org/10.1038/s41598-018-19904-y

O'Doherty, J. P., Cockburn, J., & Pauli, W. M. (2017). Learning, reward, and decision making. *Annual Review of Psychology, 68*, 73-100. http://dx.doi.org/10.1146/annurev-psych-010416-044216

Olatz, L. F., Luisa, H. S. M., & Montserrat, F. B. (2012). Spanish adaptation of the "Mobile Phone Problem Use Scale" for adolescent population. *Adicciones, 24*(2), 123-130.

Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction? *Journal of Behavioral Addictions, 7*(2), 252-259. http://dx.doi.org/10.1556/2006.7.2018.49

Pickering, A., & Gray, J. A. (2001). Dopamine, appetitive reinforcement, and the neuropsychology of human learning: An individual differences approach. In A. Eliasz & A. Angleitner (Eds.), *Advances in research on temperament*. Lengerich, Germany: Pabst Science Publishers.

Pluck, G., Bravo Mancero, P., Ortíz Encalada, P. A., Urquizo Alcívar, A. M., Maldonado Gavilanez, C. E., & Chacon, P. (2020). Differential associations of neurobehavioral traits and cognitive ability to academic achievement in higher education. *Trends in Neuroscience and Education, 18*, 100124. http://dx.doi.org/10.1016/j.tine.2019.100124

Powell, J., Dawkins, L., & Davis, R. E. (2002). Smoking, reward responsiveness, and response inhibition: Tests of an incentive motivational model. *Biological Psychiatry, 51*(2), 151-163. http://dx.doi.org/10.1016/s0006-3223(01)01208-2

Powell, J. H., al-Adawi, S., Morgan, J., & Greenwood, R. J. (1996). Motivational deficits after brain injury: Effects of bromocriptine in 11 patients. *Journal of Neurology, Neurosurgery, and Psychiatry, 60*(4), 416-421. http://dx.doi.org/10.1136/jnnp.60.4.416

Putnam, D. E. (2000). Initiation and maintenance of online sexual compulsivity: Implications for assessment and treatment. *Cyberpsychology and Behavior, 3*(4), 553-563. http://dx.doi.org/10.1089/109493100420160

Rod, N. H., Dissing, A. S., Clark, A., Gerds, T. A., & Lund, R. (2018). Overnight smartphone use: A new public health challenge? A novel study design based on high-resolution smartphone data. *PLoS One, 13*(10), e0204811. http://dx.doi.org/10.1371/journal.pone.0204811

Schultz, W. (2000). Multiple reward signals in the brain. *Nature Reviews Neuroscience, 1*(3), 199-207. http://dx.doi.org/10.1038/35044563

Shaw, H., Ellis, D. A., & Ziegler, F. V. (2018). The Technology Integration Model (TIM). Predicting the continued use of technology. *Computers in Human Behavior, 83*, 204-214. http://dx.doi.org/10.1016/j.chb.2018.02.001

Sherman, L. E., Greenfield, P. M., Hernandez, L. M., & Dapretto, M. (2018). Peer influence via Instagram: Effects on brain and behavior in adolescence and young adulthood. *Child Development, 89*(1), 37-47. http://dx.doi.org/10.1111/cdev.12838

Sheskin, D. J. (2020). *Handbook of parametric and nonparametric statistical procedures* (4th ed.). New York: Chapman & Hall.

Skinner, B. F. (1963). Operant behavior. *American Psychologist, 18*(8), 503-515. http://dx.doi.org/10.1037/h0045185

Smillie, L. D. (2008). What is reinforcement sensitivity? Neuroscience paradigms for approach-avoidance process theories of personality. *European Journal of Personality, 22*(5), 359-384. http://dx.doi.org/10.1002/per.674

Smillie, L. D., Pickering, A. D., & Jackson, C. J. (2006). The new reinforcement sensitivity theory: Implications for personality measurement. *Personality and Social Psychology Review, 10*(4), 320-335. http://dx.doi.org/10.1207/s15327957pspr1004_3

Taffel, C. (1955). Anxiety and the conditioning of verbal behavior. *Journal of Abnormal Psychology, 51*(3), 496-501. http://dx.doi.org/10.1037/h0040463

Thorndike, E. (1911). *Animal intelligence: Experimental studies*. New York: MacMillan.

Torrubia, R., Ávila, C., Moltó, J., & Caseras, X. (2001). The Sensitivity to Punishment and Sensitivity to Reward Questionnaire (SPSRQ) as a measure of Gray's anxiety and impulsivity dimensions. *Personality and Individual Differences, 31*, 837-862. http://dx.doi.org/10.1016/S0191-8869(00)00183-5

Urosevic, S., Collins, P., Muetzel, R., Schissel, A., Lim, K. O., & Luciana, M. (2015). Effects of reward sensitivity and regional brain volumes on substance use initiation in adolescence. *Social Cognitive and Affective Neuroscience, 10*(1), 106-113. http://dx.doi.org/10.1093/scan/nsu022

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

Volungis, A. M., Kalpidou, M., Popores, C., & Joyce, M. (2019). Smartphone addiction and its relationship with indices of social-emotional distress and personality. *International Journal of Mental Health and Addiction, 18*, 1209–1225. http://dx.doi.org/10.1007/s11469-019-00119-9

Vorderer, P., Krömer, N., & Schneider, F. M. (2016). Permanently online – permanently connected: Explorations into university students' use of social media and mobile smart devices. *Computers in Human Behavior, 63*, 694-703. http://dx.doi.org/10.1016/j.chb.2016.05.085

Wang, Y., Wu, L., Zhou, H., Lin, X., Zhang, Y., Du, X., … Dong, G. (2017). Impaired executive control and reward circuit in Internet gaming addicts under a delay discounting task: Independent component analysis. *European Archives of Psychiatry and Clinical Neuroscience, 267*(3), 245-255. http://dx.doi.org/10.1007/s00406-016-0721-6

Warne, R. T. (2014). A primer on multivariate analysis of variance (MANOVA) for behavioral scientists. *Practical Assessment, Research and Evaluation, 19*, 1-9. http://dx.doi.org/10.7275/sm63-7h70

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 and Review, 23*(5), 1607-1614. http://dx.doi.org/10.3758/s13423-016-1011-z

Yin, H. H., & Knowlton, B. J. (2006). The role of the basal ganglia in habit formation. *Nature Reviews Neuroscience, 7*(6), 464-476. http://dx.doi.org/10.1038/nrn1919