



Research article

Does excessive use of smartphones and apps make us more impulsive? An approach from behavioural economics

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ABSTRACT

Purpose: Problematic smartphone use has been associated with negative effects in work and school environments. This study proposes the application of a behavioural economics perspective to establish whether heavy smartphone users show a tendency to devalue the consequences of their behaviour in the long term. To address this proposition, the study sought to establish how an objective measurement of usage time of smartphones and apps might help to predict, firstly, participants' choice behaviour and, secondly, their perceived dependence levels.

Design/methodology/approach: An objective measurement of the usage time of smartphones and apps was conducted over four weeks (N = 560 data points), and a computer-based intertemporal choice task and the Spanish version of the Smartphone Addiction Inventory (SPAI) were applied. The participants were twenty undergraduate college students.

Findings: Although the usage time of devices and apps failed to predict the choice behaviour, a correlation was found between the total usage time of smartphones and WhatsApp and Facebook apps and users' dependence level. On the other hand, dependence had a positive effect on the average selection of the impulsive choice.

Originality/value: This paper proposes the application of a behavioural economics perspective to explore the relationship between objectively measured usage time of smartphone and apps, choice behaviours in an intertemporal task and users' perceived dependence levels. This allows us to consider an alternative to the traditional psychiatric approach in an environment of increasing access to and use of mobile digital platforms.

1. Introduction

The use of smartphones has increased significantly in recent years, allowing not only immediate communication with other people -phone calls, texting and social media- but also facilitating daily task-oriented activities, such as online banking or m-commerce (Kim et al., 2018). In 2019, the average time of daily internet use at global level was of 6 h and 43 min (Kemp, 2020), with mobile devices accounting for more than half of this consumption, estimated at 3 h and 40 min, and mobile applications (apps) representing more than 90% of the total mobile activity time (App Annie Intelligence, 2020). Studies conducted almost a decade ago showed that mobile phones were having a positive impact on users at

level of social interaction, improvement of quality of life and inclusion of vulnerable populations with apps which enabled immediate communication, access to educational tools and content, betterment of physical activity, disease treatment (m-health), improved equity and accessibility in urban mobility, and global connectivity. However, studies published recently have focused on the possible negative effects of the use of smartphones, producing an increased amount of evidence in terms of the existence of a series of negative consequences related to excessive use of smartphones, including sleep disorders, anxiety, depression (Lian et al., 2016; Lee et al., 2018), nomophobia (Arora and Chakraborty, 2020), and negative consequences in the workplace, such as work-home interference and burnout symptoms, specifically among heavy users of smartphone

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after work hours (Derks and Bakker, 2014) and in academic settings, due to decreased academic performance associated with sleep issues, lack of concentration, stress and anxiety (Samaha and Hawi, 2016). On the other hand, a more recent research trend has inquired into the habits and frequency of use of smartphones in different countries. For instance, a study in Spain established that users check their smartphone an average of 150 times a day; in addition, 80% of the participants indicated that, when they sleep, the device remains next to the bed (Simó-Sanz et al., 2018). Another study in the United States measured the use of smartphones for a week and found -for a sample of adolescents-that the average daily use of smartphones was of 243 min, that is, a little more than 4 h a day, and the number of screen unlocking actions was 88 times a day on average (Rozgonjuk et al., 2018). A different study found that 60% of users cannot spend an hour without checking the notifications on their smartphone, 54% use this device while lying in bed and 30% use it very often while having a meal with other people (Hussain et al., 2017).

In terms of the relationship between an excessive use of smartphones and the negative consequences mentioned before, some authors have identified symptoms in heavy users which are similar to those observed in patients who are addicted to different substances (Billieux, 2012). In fact, many studies have addressed problematic smartphone use from a psychiatric perspective, seeking to correlate the dependence levels measured through self-reports that have psychological variables (psychological traits) by applying scales that have been well established in the literature (Lee et al., 2014; Nahas et al., 2018). However, in the first place, these studies have only used data attained through cross-sectional designs and have failed to incorporate objective and longitudinal measurements concerning the use of smartphones; in the second place, they have applied self-report scales to establish a possible addiction, disregarding alternative methodologies. In addition, there is a lack of consensus regarding whether the existence of an addiction or, more specifically, a behavioural addiction can be considered (Panova and Carbonell, 2018; Yu and Sussman, 2020). Furthermore, very few studies have addressed this issue from a behavioural perspective to establish if users who use smartphones for a longer time have low levels of self-control. This means that individuals who show problematic smartphone use may be characterized by a noticeable preference for a behaviour that generates immediate consequences with high utility (entertainment or social interactions) but that in the long term is associated with very harmful effects on personal, social and even financial levels (Foxall, 2016). These situations correspond to the concept of delay discounting, defined as the devaluation of future consequences of behaviour. As the consequence moves further into the future, it has less influence over the present decision (Madden and Johnson, 2010). The changes that occur in the subjective value of the alternatives at different moments of time are known as intertemporal choices. Through this process, a subjective value of the reward is established, combining its magnitude and the delay with which it will be delivered (Peters and Büchel, 2011). Therefore, this study seeks to address this gap in the literature, establishing a possible relationship -through different techniques-between the level of use of smartphones and apps and a pattern of impulsive choice, characterized by favouring positive yet immediate consequences. To achieve it, it is convenient to take into account the measurement techniques used to determine the levels of use of these mobile digital services, as well as the methods to establish a choice pattern (self-controlled or impulsive). Although this approach can be considered exploratory, it may offer relevant information on the impact of the use of this technology in other types of choice behaviours.

Regarding the identification of levels of use, and specifically those of the heavy users, recent studies have incorporated techniques for measuring the use of smartphones that allow access to objective data: from the use of apps designed to measure the device's usage time to apps that count the number of screen unlocking actions occurring during the day (Esmaeili Rad and Ahmadi, 2018; Rozgonjuk et al., 2018; Wilcockson et al., 2018). This type of measurement has been suggested as an alternative for comparing results with those of previous cross-sectional

studies (Meng et al., 2020). More importantly, though, is the recent finding indicating that there is a significant difference between the users' self-reported data and the usage data automatically collected by these apps (Lee et al., 2018). Thus, this study sought to explore whether heavy smartphone users show a tendency to devalue the consequences of their behaviour in the long term by examining the relationship between the usage time of their smartphone and some categories of apps and data from a consumer choice task as a measure of self-control as well as data from a well-established screening test for problematic smartphone use. It is expected that it could contribute to an understanding of this phenomenon by contrasting a more contextual approach, typical of behavioural economics, with the psychiatric approach, characterized by posing the conception of addiction as an internal state.

2. Theoretical background

Three relevant literature trends were identified for this study, the first is related to the conceptualization and theoretical frameworks applied to the study of smartphone addiction. The second deals with the background of behavioural economics in order to address phenomena of excessive consumption, particularly in the sphere of services, which, from the perspective of psychiatry and clinical psychology, correspond to behavioural addictions. And the third is related to the background in the study of the recent concept of problematic smartphone use. This review intends to establish the background in the study of the phenomenon, key aspects of each stance and the way in which the phenomena of problematic smartphone use can be related with a more impulsive choice behaviour pattern. The following are the three sections and their respective hypotheses.

2.1. Conceptualization and theoretical frameworks applied to the study of smartphone addiction

There are several definitions related to this category of behaviour within the academic literature, including, initially, the concept of mobile phone addiction, which consists of a lack of ability to control the desire to use the mobile phone (Walsh et al., 2010). Subsequently, the concept rapidly evolved towards smartphone addiction, which is defined as the inability to control the impulse to excessively use the smartphone, with consequent negative results for the user's quality of life (Sun et al., 2019). More recently, the term problematic mobile phone use (PMPU) emerged to account for this phenomenon. However, the definition does not differ much from that previously provided for mobile phone addiction. So, problematic use has been defined as the inability to regulate the use of the mobile phone, which generates negative consequences in the daily life of the individual (Billieux, 2012).

Despite the variability in the phenomenon's characterization, some studies provide a theoretical foundation for the possible addiction to the smartphone. In the first place, the general strain theory proposes that problematic or excessive behaviours are due to the negative consequences caused by high levels of stress coming from different sources. The lack of achievement of goals, the inability to maintain stimuli that are positive for the person, as well as exposure to situations perceived as negative, constitute sources of stress that can trigger addictive behaviour (Agnew, 2001). It is important to note that this theory was initially developed for the interpretation of criminal behaviours and was later applied to the field of addictive behaviours (Jun and Choi, 2015). Therefore, according to it, excessive use of smartphones comes from high levels of stress perceived by users (Gao et al., 2018; Liu et al., 2018).

Secondly, the relationship between self-control and smartphone addiction has been proposed as a theoretical possibility in this field. Specifically, the theory of self-regulation states that the lack of self-regulation in the use of smartphones is due to low self-control, which makes users unable to counteract the craving to interact with the device, which, by the way, is almost always available to be used (Gökçearslan et al., 2016). A third theoretical framework is the compensatory Internet

use theory (CIUT) (Kardefelt-Winther, 2014), this theory states that addictive behaviours are generated by different motivations, among which the most important is stress. People who perceive high levels of stress can find a solution to alleviate that negative emotional state in the use of technology, in this case in digital services available on their smartphone. This can drive people who have high levels of depression or anxiety to increased use of the smartphones with the intention to relieve perceived stress and thus regulate their emotional states. Therefore, according to this theory, the use of smartphones would become an alternative to escape stress and its negative consequences (Rozgonjuk et al., 2018).

Other efforts have been channelled to the exploration of possible mediating variables for problematic smartphone use; those that have received most attention so far are sex and age. With respect to sex, it has been found that men tend to use smartphones for communication in a business or professional context, while women use it for general networking (Lee et al., 2014); as for university students, factors associated with smartphone addiction in men include the use of game apps, poor sleep quality and anxiety, and in women the use of multimedia and social media apps, depression and anxiety (Chen et al., 2017). However, recent review articles have suggested that the evidence of possible gender-based differences is not conclusive (Cho, 2020; Busch and McCarthy, 2021). Furthermore, regarding age, it has been suggested that the younger population has higher prevalence of problematic smartphone use. In fact, a considerable amount of studies have focused on adolescents and young adults (Aslam et al., 2018; Chen, 2018; Liu et al., 2018; Sun et al., 2019).

Despite increased literature on the topic, especially since 2017, there is no unifying theory given the phenomenon's complexity (Yu and Sussman, 2020), which can be added to the methodological challenges to define valid measurements of the use of smartphones and apps. Addressing these aspects would allow identifying factors that could contribute to the interpretation of excessive use of smartphones from alternative theoretical perspectives and measurement techniques that would go beyond survey-based self-reports (Wilmer et al., 2017; Busch and McCarthy, 2021). In that sense, advances in behavioural economics can contribute to understanding this major topic amidst this new technologically-advanced era.

2.2. The behavioural economics approach to the study of excessive consumption

The behavioural economics approach considers addiction or dependence as a pattern of choosing one behaviour over others available at a time in a particular context, so that it is possible to influence it through rewards and costs associated with each behavioural alternative (Ross et al., 2008). Therefore, it is possible that heavy smartphone users show a high rate of temporal discounting related to future consequences associated with alternative behaviours, which may be evident in the anxiety, sleep, work, and academic performance problems mentioned above.

Consumers face daily multiple-choice situations involving different rewards with different discounting intervals. In their simplest form, these situations entail choosing between an option that provides a small but sooner reward (SSR) and another that offers a larger but more delayed option (larger later reward or LLR) (Arfer and Luhmann, 2015). These situations can be routine decisions such as choosing between eating an ice cream (SSR) or staying on a diet (LLR), saving to pay for college tuition (LLR) or going out for an expensive meal with friends (SSR), taking a day off at the club or studying for an exam the next day.

In terms of methodology, research on temporal discounting has applied a procedure known as intertemporal choice task, in which participants must choose between two monetary rewards (hypothetical or real), one is immediately available (SSR) and the other, of greater magnitude, is available at a future time (LLR). This procedure implies that the SSR is modified successively in each trial while the LLR is kept constant. Results have allowed establishing the current subjective value

of an SSR that is equivalent to the LLR, that is, it is indifferent to the person, over a series of specific delay discounting values (Critchfield and Kollins, 2001). With respect to hypothetical or real rewards, evidence in the literature indicates that there are no significant differences in the choice patterns between these two conditions (Whelan and McHugh, 2010).

Results of research on temporal discounting indicate that high discount on the subjective value of future consequences is associated with an impulsive choice, which consists of the preference for a small but immediate result instead of a larger but more distant outcome (Ross et al., 2008; Daugherty and Brase, 2010; Davis et al., 2010; MacKillop et al., 2011). There is evidence that steep delay discounting is associated with different problems that have high social impact at the levels of substance abuse and behavioural addictions (MacKillop et al., 2011), obesity (Davis et al., 2010) and other healthy prevention behaviours (Daugherty and Brase, 2010). This type of evidence indicates a reliable relationship between steep delay discounting and a set of behaviours that result in adverse effects on health in the long term, thus becoming a process that occurs transversally to these problematic behaviour patterns (Rung et al., 2018). However, another behavioural trend, known as preference reversal, occurs along with temporal discounting. The two are closely related yet not identical. Preference reversal corresponds to the choice of the alternative that offers an immediate reward, reflecting rejection of the waiting time for the option that provides a bigger reward but one that is distant in time, while steep discounting implies an abrupt reduction of the subjective value of the LLR because it will not be available for a considerable time (Foxall and Sigurdsson, 2012). Therefore, it is relevant to establish whether the usage time of smartphones and apps may be related to more impulsive choice behaviours given that frequent use of devices may favour a pattern of behaviours that values the immediate experience of access to information, entertainment or socialization provided by apps to the detriment of other behaviours that offer greater long-term benefits. Therefore, we hypothesize that:

H1. As the usage time of smartphones and apps increases, users will present greater impulsiveness in the intertemporal choice task.

Accordingly, it is relevant to consider the advances in the study of addictions carried out in the research programme of behavioural economics, particularly from the theoretical and methodological perspectives in the study of temporal discounting (Peters and Büchel, 2011; Rung et al., 2018). This approach enabled the researcher to carry out longitudinal studies based on real use data for both smartphones and apps.

2.3. Problematic smartphone use

Although a problematic use of mobile phones was already under consideration at the beginning of this decade (Walsh et al., 2010), the concept rapidly evolved towards problematic smartphone use (PSU), defined as the inability to regulate the use of a smartphone, which generates negative consequences in the user's daily life, including aspects related to behaviours in certain contexts and to potential negative consequences of inappropriate or excessive use, which include negligent use (i.e., use while driving), use in prohibited places (e.g. theatres and libraries) and dependence on the use of the device, which leads to an excessive need for use that becomes evident, for example, in the constant checking of notifications (Billieux, 2012; Shankar, 2016; Lopez-Fernandez et al., 2018; Barnes et al., 2019; Sun et al., 2019).

Another important aspect concerns the growing interest of many authors in developing different measurement instruments to establish the prevalence of a possible addiction or problematic smartphone use. Some of the scales applied in recent studies include the Mobile Phone Addiction Index (MPAI) (Liu et al., 2018), the Smartphone Addiction Inventory (SPAI) (Simó-Sanz et al., 2018), the Test of Mobile Dependence (TMD) (Fransson et al., 2018), the Smartphone Addiction Scale (SAS) (Rozgonjuk et al., 2018; Sun et al., 2019; Laurence et al., 2020), the Mobile Phone Problematic Use Scale (MPPUS) (Nahas et al., 2018), as well as scales designed to measure related constructs such as nomophobia

(Yildirim and Correia, 2015). These scales, by definition, are based on the interviewee's self-reporting to establish not only the incidence of problematic use but also the personality traits that may be associated with such behaviour. Therefore, mainstream research on the subject has focused on searching for relationships between personality factors and level of use reported by participants. Based on this background, some authors have raised the need for further research to objectively establish the usage time of smartphones and the implications that this has for the concepts of addiction and problematic use and the theories that can account for this phenomenon (Esmaeili Rad and Ahmadi, 2018; Wilcockson et al., 2018; Meng et al., 2020). Therefore, it is essential to explore the relationship that may exist between usage time of smartphones and apps, measured objectively within a longitudinal time frame, and smartphone dependency levels, measured through a screening test. Thus, we propose the following hypothesis:

H2. As the usage time of smartphones and apps increases, dependence on smartphones will become greater.

A more recent line of research suggests that possible problematic use takes place not only in terms of the physical device as such but in relation to the content and the activities that the users perform in it. Therefore, the combination of smartphones' technological attributes, such as portability, connectivity and personal use, coupled with access to information, content, socialization and other multiple benefits offered by web browsing and apps, has led to a global increase in usage according to the aforementioned statistics. In that regard, authors such as Panova and Carbonell (2018) and (Barnes et al., 2019) have mentioned the need to start investigating whether what actually exists is problematic use of the device or, on the contrary, of the contents or apps to which users have access, as well as the relationship that exists between these two behaviours: use of the smartphone and use of the apps and web browsing. In a recent study, which maintained the conceptual stance of addiction, differences were sought between the level of addiction to smartphones and the level of addiction to social networking apps, finding that there is greater addiction to smartphones than to social networking apps, with significant differences according to the users' educational attainment (Barnes et al., 2019). This raises the possibility that a high level of dependence on smartphones may be related to higher levels of impulsive responses, which is why we propose the following hypothesis:

H3. As the dependence on smartphones becomes greater, the impulsiveness in the choice situation will be greater.

Taking the aforementioned background into account, this research aims to establish the relationship of smartphone and mobile apps usage behaviour with the consumer's choice behaviour in a situation of temporal discounting. Thus, the main objective of the study is aimed at establishing if there are differences with respect to the temporal discounting (impulsiveness) in a situation of choice for users who have different levels of use or dependence on smartphone or mobile apps. That is, it seeks to understand the way in which consumers' choice behaviour is influenced by the level of dependence on smartphones or apps. In order to follow this objective, the next section describes the applied methodological strategy, results obtained for each of the hypotheses, and discussion and conclusions, emphasizing on the implications at theoretical and methodological level.

3. Research methodology

3.1. Design

This study adopted a pragmatic, deductive and quantitative approach, applying a cross-sectional survey design (Creswell, 2013) and a longitudinal measurement based on real use data for both smartphones and apps (Esmaeili Rad and Ahmadi, 2018; Rozgonjuk et al., 2018; Wilcockson et al., 2018; Grimaldi-Puyana et al., 2020). This, together with the possibility of applying a methodology that contains a delay discounting task (Tang et al., 2017), allowed the comparison of these results with those obtained through a screening scale (Simó-Sanz et al., 2018).

To do so, a cross-sectional survey was conducted in the first place to measure smartphone dependence. It was followed by an intertemporal choice task to establish participants' level of self-control and impulsiveness. Then, a behavioural record of longitudinal nature was applied to obtain objective measurements of usage time of the device and apps. Other methodological aspects of interest are described below.

3.2. Participants

The study was conducted in Bogota, Colombia and the sample consisted of twenty students from Politecnico Grancolombiano, a large private university (thirteen women, average age = 21.2 years, range = 19–26). They were recruited through a call to the main campus and received academic credits for their participation in the study. This sample size was deemed adequate for our analyses as extensive smartphone usage time data were collected for each participant throughout the four weeks of duration of the usage time record of smartphones and apps, which (as seen in the Measurement section) resulted in the collection of 560 data points, corresponding to the twenty participants in the 28-day period of continuous record. This can be considered a small-N design, since it attains a large number of observations of a relatively small number of participants (Smith and Little, 2018), which has been vindicated lately by psychological literature due to the fact that it allows a significant number of measurements that facilitate research of systematic and functional relationships between behavioural events manifested at the level of individual participants (Normand, 2016; Grice et al., 2017; Little and Smith, 2018). This sample design has been applied in contexts such as the use of mobile apps promoting physical activity (Rabin and Bock, 2011), the use of mobile touch-screen devices by people with developmental disabilities (Stephenson and Limbrick, 2015) and the effect of the use of smartphones on daily work-home interference (WHI) (Derks and Bakker, 2014).

3.3. Measurement

3.3.1. Intertemporal choice task

The participants were informed about the nature and procedure of the task. The instructions that they received were as follows:

Welcome to our experiment! In this task, you must conduct a series of choices with fictitious money. There are no right or wrong answers; you just have to choose the one you prefer. To do this, you must press "F" if you prefer the option that appears on the left, while pressing "J" means you prefer the option that appears on the right. The decisions you make will not affect you obtaining the incentive offered for your participation, but please reflect and make each choice as if it were real money.

The experiment was presented in E-Prime 3.0, and the task was presented in Spanish. Based on previous evidence indicating that there are no systematic differences in the degree of delay discounting estimated through the titrating sequence and fixed sequence procedures, the latter was used for the presentation of immediate rewards within each trial (Odum et al., 2006; Rodzon et al., 2011). The design of the experimental conditions used fictitious rewards, since previous evidence indicates that there are no significant differences in devaluation responses in delay discounting studies when using real or fictitious money (Bickel et al., 2009). As proposed by Tang et al. (2017), the computer-based task consisted of 63 trials, including two for participants to become familiar with the procedure. In the experimental trials, the presentation of the alternatives was counterbalanced between the left and the right of the screen and the following variables were manipulated: waiting time for small-sooner (SS) options (today, 3 and 6 months), waiting time for larger-later (LL) options (6, 9 or 12 months). The reward values for the SS options were of 5,000 pesos (about 1.5 dollars), 10,000 pesos, 15,000 pesos, 20,000 pesos, 25,000 pesos, 30,000 pesos, 35,000 pesos, 40,000

pesos, 45,000 pesos (about 13 dollars), and the reward value for the LL options was of 50,000 pesos (about 15 dollars). Through the trials, every amount from 5,000 to 45,000 pesos was repeated seven times, and the 50,000 pesos value was repeated 63 times. Thus, there were nine magnitude categories of Δ Amount (Δ represents the difference between the SS and LL reward values) and four categories of Δ Time (Δ represents the difference between waiting time for the SS and LL options). Regarding the intertemporal conditions, seven delay discounting categories were established: 3 months vs. 6 months, 6 months vs. 9 months, 3 months vs. 9 months, 6 months vs. 12 months, today vs. 9 months, 3 months vs. 12 months and today vs. 12 months. Participants had to choose the preferred option, whichever it was it was coloured in red to indicate that the choice had been made. Figure 1 shows the sequence of visualization of the choice task displayed in the screen; in this trial, Δ Time was of 12 months and Δ Amount was of 40,000 pesos. Stimuli pairs were randomly displayed, for a total of 63 choice conditions (see Appendix I).

3.3.2. Problematic smartphone use

The Spanish version of the Smartphone Addiction Inventory (SPAI), as validated by Simó-Sanz et al. (2018), was applied to measure the Problematic Smartphone Use reported by participants (See Appendix II). This version showed adequate levels of validity through goodness of fit indices as well as good reliability of the global inventory and each of its corresponding factors: compulsive behaviour, functional impairment, abstinence, and tolerance. The Cronbach's alpha coefficient for the SPAI was 0.94, and the Cronbach's alpha coefficient in our sample was 0.95. For the four subscales, the Cronbach's alpha coefficient in our sample was 0.87 (for compulsive behaviour), 0.87 (for functional impairment), 0.82 (for withdrawal) and 0.88 (for tolerance). The instrument consisted of 26 items, with responses given on a four-point Likert scale. Therefore, the possible scores for the inventory ranged from 26 to 104.

3.3.3. Measurement of smartphone and app usage time

The StayFree[®] app (available for Android operating systems on the Google Play Store platform) was applied. This app measures daily usage time of installed apps and total smartphone usage time. It also generates valid measurements regarding the use of the smartphone (Sarun et al., 2019). Just like other apps used in similar studies (e.g. Moment[®], for iOS operating systems; Rozgonjuk et al., 2018), StayFree[®] registers the usage time for which the screen is active in each app. Each participant received personalised support for installing the app and information about how it operates in the device. Participants were told that the period of measurement would be of four weeks, thus doubling the period of measurement used by Wilcockson et al. (2018). Moreover, they received a demonstration on how to generate the report on the device's use, which is a file in Microsoft Excel[®]. The process had to be conducted once a week and the initial measurement day was the day after the app was installed. Follow-up e-mails were sent to the participants on a weekly basis as reminders of the timely delivery of reports on corresponding days. The app's report includes the days (Monday, Tuesday, etc.) in the columns, and the apps installed in the device can be found in the rows. Cells show the usage time for each app for the day in hours, minutes, and seconds.

Total usage time for each app appears in the lower part of the columns, and the last row shows the device's total usage time per day. This is how the total usage time was calculated for each app and for the device in the four weeks that were recorded. All of the values were registered in seconds with the aim of having a unit of time that was amenable for the analysis.

3.4. Procedure

Participants who willingly became part of the study were summoned to an initial session in a computer room, during which the Intertemporal Choice Task was applied, followed by the SPAI-S. This procedure lasted for approximately 30 min per participant. When it ended, each person was scheduled for another session in which he or she was assisted with downloading and using the StayFree[®] app and it was explained how to generate and forward the reports from the app regarding the use of the smartphone via e-mail.

3.5. Statistical analysis

Statistical analyses were conducted with the SPSS 22.0 software. To test the effect of smartphone and app usage time on intertemporal choice, a logistic regression analysis was applied. This technique was used to identify the factors that allow predicting membership values of two possible groups (Hair Jr. et al., 2013). This case sought to establish whether there are factors that allow discrimination between impulsive responses (SSR) and self-controlled responses (LLR). To estimate the logistic regression equation, the logit function was calculated first; this consisted of the natural algorithm of the odds of having a positive response, in this case, self-controlled choices (LLR).

3.6. Ethics

The study protocol was approved by the institutional research ethics committee at Institucion Universitaria Politecnico Granacolombiano (2018-FMCAMI+286805), and all of the participants provided a written informed consent voluntarily and were able to view example data in advance.

4. Results

4.1. Descriptive statistics

The consolidated record of all the participants showed a total of 619 different apps, with an average of 68.6 (standard deviation [SD] = 20.8) apps installed in each smartphone. The average daily hours of use were 4.1 (standard deviation [SD] = 1.79). Table 1 describes the top five apps with the highest usage time. These apps represent 71.2% of the total usage time of the smartphones, accounting for average daily use of 2.95 h.

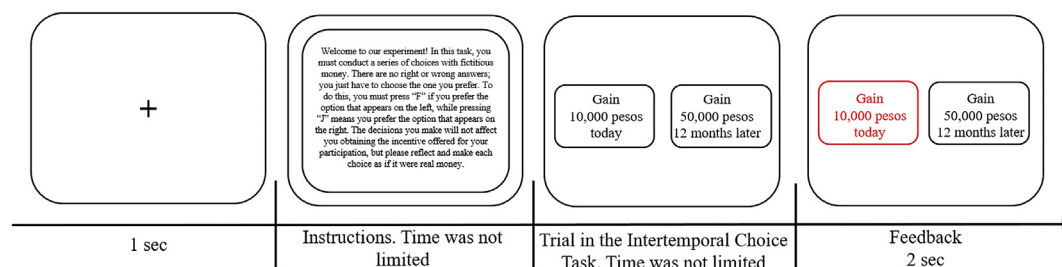


Figure 1. Procedure for a trial within the Intertemporal Choice Task.

Table 1. Smartphone and app usage time.

App	Total Usage Time*	Share	Average Daily Hours of Use	Average Daily Minutes of Use
WhatsApp	2314509	27.7%	1.15	68.88
Instagram	1231187	14.7%	0.61	36.64
YouTube	1130289	13.5%	0.56	33.64
Facebook	656203	7.9%	0.33	19.53
Chrome	611541	7.3%	0.30	18.20
Total Usage Time of the Top Five Apps*	5943729	71.2%	2.95	176.90
Total Usage Time of other Apps*	2406575	28.8%	1.19	71.62
Total Usage Time of the Smartphone*	8350304	100.0%	4.14	248.52

* Usage times measured in seconds (sec.). Source: own elaboration.

4.2. Effect of smartphone and app usage time on intertemporal choice

The results described in Table 1 led to the identification of the apps with the highest usage time, which, along with the total usage time of the smartphone, were established as predictor variables. The data of these temporary variables were recorded in seconds to ease the analyses by providing a quantitative variable of a continuous type. On the other hand, choice was considered to be the criterion variable and had two possible responses (SSR and LLR) in each of the 63 choice situations within the intertemporal choice task. Therefore, each participant had 63 choice responses, which were coded as follows: a value of zero if the SSR alternative was chosen (impulsive response) and a value of one if the LLR alternative was chosen (self-controlled response). Age and gender were also considered as possible moderator variables. This analysis seeks to respond to H1. The data matrix consisted of 1,134 rows corresponding to the choice responses of eighteen participants, since two participants selected the SSR option (value of 0) in all of the conditions, which could affect the analysis. The results of the logistic regression are shown in Table 2.

The equation obtained was the following:

$$\text{Ln}(p / 1-p) = \text{Log}(\text{odds in favour of self-controlled choice}) = -2.119 + 0.000 \text{ Time on Instagram} + 0.171 \text{ Total Time on the Smartphone} + 0.269 \text{ Total Time on the Apps of Interest} + 1.186 \text{ Time on Chrome} + 0.155 \text{ Time on WhatsApp} + 0.378 \text{ Time on YouTube} + 0.282 \text{ Time on Facebook} + 0.089 \text{ Age} + 0.002 \text{ Gender}$$

The results of the Wald test (Hair Jr. et al., 2013) revealed that two of the variables introduced into the model discriminated between impulsive and self-controlled choices ($p < .05$), usage time of Instagram and age. However, upon examination of the β value of the time spent on Instagram, no changes in the choice values ($\beta = 0.000$) were observed insofar as, for every year of age ($\beta = 0.089$), there was a 0.09 increase in the probability of choosing the self-controlled choice (LLR) (Table 2, factor X8: age). These results indicate that the null hypothesis for this effect (H1) should not be rejected.

In terms of the Hosmer and Lemeshow goodness-of-fit test ($p = 0.004$), it can be concluded that, due to its significance, the model does not fit well among the frequencies of cases observed and the frequencies of forecast cases. Considering the classification adjustment foreseen in the model, Table 2 shows greater sensitivity to the correct classification of impulsive responses (70%), but it is extremely low for self-controlled responses (37%), with an overall percentage of 54%. On the other hand,

Table 2. Logistic regression results.

Factor	B	SE	Wald	df	Sig.	Exp. (β)
x1: Time on Instagram	0.000	0.000	4.866	1	0.027*	1.000
x2: Total time on the Smartphone	0.171	0.237	0.205	1	0.679	1.037
x3: Total time on the Apps of interest	0.269	0.115	0.815	1	0.604	1.165
x4: Time on Chrome	1.186	0.057	1.231	1	0.276	1.287
x5: Time on WhatsApp	0.155	0.368	0.973	1	0.693	1.004
x6: Time on YouTube	0.378	0.149	1.258	1	0.539	1.114
x7: Time on Facebook	0.282	0.233	1.116	1	0.596	1.058
x8: Age	0.089	0.032	7.61	1	0.006*	1.093
x9: Gender (female)	0.002	0.021	0.849	1	0.965	1.071
Constant	-2.119	0.720	8.664	1	0.003*	0.120
Goodness-of-fit tests	χ^2		Df		Sig.	
LR test	4.884		1		0.027	
Hosmer and Lemeshow test	22.785		8		0.004	
Pseudo R ² measures						
Count R ²	0.025					
Cox and Snell R ²	0.008					
Nagelkerke R ²	0.011					
Classification Table	Predicted					
Observed	Impulsive (SSR)		Self-controlled (LLR)		Percentage correct	
Impulsive (SSR)	407		174		70.1	
Self-controlled (LLR)	349		204		36.9	
Total	756		378		53.9	

Notes: * Significant at 5 percent level.

Source: own elaboration.

the pseudo R² measures, such as the Count R², Cox and Snell R² and Nagelkerke R², initially show no variance explained by the model.

4.3. Relationship between smartphone and app usage time and perceived dependence on smartphones

An initial correlation analysis was conducted to establish a relationship between the variables -corresponding to H2-. Table 3 shows that the dependence on smartphones (SPAI score) was correlated with the total usage time of the smartphone and with the usage time of the WhatsApp and Facebook apps.

Furthermore, a multiple regression analysis was performed with the aim of proving these interactions. Thus, perceived dependence on the smartphone (SPAI score) acted as the dependent variable and the usage time of the device and apps acted as the independent variables. Table 4 shows that the F value was of 5.75, which was significant at the level of 0.05 (p = 0.029). The only independent variable with a significant and positive effect was the total usage time (p = 0.029). The adjusted R² value was of 0.27; thus, the total usage time of the smartphone explains 27% of the perceived dependence on the smartphone. No other usage time of the apps had a significant effect on perceived dependence. Therefore, these results support the hypothesis (H2) that, as usage time of smartphones increases, perceived dependence increases as well. The equation obtained was:

$$\text{Perceived Dependence on the Smartphone} = 39.13 + 0.0000407 \text{ Total Usage Time}$$

4.4. Relationship between perceived dependence on the smartphone and intertemporal choice

Then, a lineal regression analysis was conducted with perceived dependence on the smartphone (SPAI score) as the independent variable and the average responses given by each participant in the 63 choice conditions as the dependent variable, which corresponds to H3. A value of 1 for impulsive responses (SSR) was assumed in this case. Table 5 shows that the F value was of 5.31, which was significant at the level of 0.05 (p = 0.034). Perceived dependence had a significant and positive effect on the average choice of the impulsive response (p = 0.029), as, for every increase point in the SPAI value obtained, there was a 0.5 increase in the percentage of selected impulsive choices. The adjusted R² value was 0.23; thus, perceived dependence on the smartphone explains 23% of the intertemporal choice. Therefore, these results support the hypothesis (H3) that, as dependence on smartphones increases, users' choice impulsiveness increases as well. The equation obtained was:

$$\text{Intertemporal Choice} = 0.25 + 0.005 \text{ Perceived Dependence on the Smartphone}$$

5. Discussion

5.1. Key findings

The objective of this study was to contribute to the literature in the area by incorporating objective measurements on usage time of smartphones and apps and applying a methodology based on behavioural economics to explore a possible pattern of impulsive choice related to increased use of smartphones and apps.

Regarding this possible relationship, the usage time of smartphones or apps was found to have no effect on the users' intertemporal choice. Although the results evince a significant effect of the usage time of the Instagram app and age as mediating variables, the R² variables fail to show variance explained by the model when applying logistic regression as an analysis technique. These results do not confirm the first hypothesis. An aspect to consider concerning this finding is that, as in the study by Tang et al. (2017), the intertemporal choice task used differed from the designs based on the titration method, which have been applied in prior studies, as described by Rodzon et al. (2011).

On the other hand, interestingly, a correlation was found between the total usage time of the smartphone and the WhatsApp and Facebook apps and the smartphone dependence level obtained with the SPAI-S score. This finding concurs with Rozgonjuk et al.'s (2018) finding in terms of the correlation between problematic smartphone use (PSU) and average minutes of screen time over a week. Nevertheless, the cited study did not consider usage time of the apps, hence the relevance of the finding that shows that two of the global top five apps according to App Annie Intelligence (2018) have usage times that significantly correlate with smartphone dependence in the analysed sample. In addition, the consistency between the results from the point of view of the measurement's temporary framework is noteworthy; the study by Rozgonjuk et al. (2018) considered only a week's record, whereas the present study obtained usage times throughout four consecutive weeks. Additionally, the multiple regression analysis found a significant and positive effect of total usage time on smartphone dependence, while the specific usage times per app failed to show a significant effect, a result that is consistent with the findings of Barnes et al. (2019). This leads to the interpretation that smartphone dependence does not rely on the use of any particular app (although two of the apps showed significant bivariate correlations) but that the joint usage of the apps as a whole seems to have an effect on users' reported dependence. These findings confirm the second hypothesis.

Moreover, smartphone dependence had a significant and positive effect on the average of impulsive choice behaviour (SSR). This result is similar to that of Tang et al. (2017), although these authors performed a Pearson correlation of the scores obtained using the SPAI and BIS scales. The latter, named the Barratt Impulsiveness Scale, intends to measure a general impulsiveness trait, and is made up of 30 items. They found a positive relationship (R² = 0.223, p = 0.012) with an explained variance

Table 3. Correlations of usage time (SP and apps) with perceived dependence (SPAI score).

Variable	Variable Descriptors			Correlation with SPAI Score	
	Mean	St. Dev.	n	Pearson's r Coefficient	p-Value
SPAI Score	58.05	15.56	19	1.00	
Total Usage Time	425907.8	181927.89	19	0.51	0.02*
Chrome	30002.63	39236.08	19	0.11	0.52
WhatsApp	120198.47	79111.46	19	0.44	0.09**
YouTube	58188.42	81390.12	19	0.01	0.79
Instagram	62538.63	47181.27	19	0.11	0.81
Facebook	33930.42	39815.04	19	0.45	0.06**

* p-Value ≤ 0.05; ** p-Value ≤ 0.10.

Source: own elaboration.

Table 4. Multiple regression analysis of usage time on perceived dependence on smartphone.

Dependent Variable	Independent Variable	β	t-Value	p	R ²	F
Perceived dependence on smartphone	Total Usage Time	4.08E-05	2.4	0.029*	0.27	5.75**
	WhatsApp	0.19	0.75	0.462		
	YouTube	-0.43	-1.66	0.116		
	Instagram	-0.31	-1.23	0.235		
	Facebook	0.34	1.64	0.120		
	Chrome	-0.48	-0.20	0.844		

* p-Value \leq 0.05.** Significant at 5 percent level ($p = 0.029$).

Source: own elaboration.

Table 5. Linear regression analysis of perceived dependence on intertemporal choice.

Dependent Variable	Independent Variable	β	t-Value	p	R ²	F
Intertemporal Choice	Perceived dependence on smartphone	0.005	2.3	0.034*	0.23	5.31

* p-Value \leq 0.05.

Source: own elaboration.

value that nears that obtained by this study ($R^2 = 0.23$, $p = 0.034$), indicating that the higher the reported level of dependence, the larger the percentage of impulsive choices. This finding is relevant also because this relationship is established through data obtained in a choice test, unlike the previously mentioned study that applied a screening scale to determine impulsiveness as a personality trait. This opens the possibility to continue exploring the relationship between the use of mobile services and a choice pattern based on the concept of temporal discounting from the perspective of behavioural economics. On the other hand, in terms of variables of gender and age, no significant differences were found between men and women, and although a positive relationship was initially found between age and a more self-controlled choice pattern, statistical hypothesis testing was not significant. Regarding other scales, and the questionnaire on nomophobia (NMP-Q) in particular (Yildirim and Correia, 2015), similarities are observed in the factors of not being able to communicate and losing connectedness of the NMP-Q and the functional impairment factor of the SPAI, as both cases evince impact on social and familial life, and even academic or work performance. These results provide additional evidence by finding a significant effect of users' reported smartphone dependence on the choice responses in an intertemporal choice task. Thus, an additional step was taken by incorporating a response to a set of intertemporal choice situations as a criterion variable, allowing this methodological alternative to be considered for future research on the relationship between smartphone dependence and users' intertemporal choice pattern.

5.2. Theoretical implications

Based on suggestions in the literature on behavioural addictions, the possibility that smartphone usage time could predict participants' responses in an intertemporal choice task was proposed. To address this question, one of the study's contributions consists of incorporating, firstly, an objective measurement of the usage time of smartphones and apps over a period of four weeks, which exceeds the time reported by previous studies (Esmaili Rad and Ahmadi, 2018; Rozgonjuk et al., 2018; Wilcockson et al., 2018) and matches that reported by Lee et al. (2018), and, secondly, the use of an intertemporal choice task as an alternative to measure the effect of the quantity and delay of a set of rewards on participants' choices. Although it was found that the total usage time had a positive and significant effect on dependence of smartphones (a fact that supports the second hypothesis), it failed to have any effect on intertemporal choice (which resulted in a lack of support for the first hypothesis). The overall results provide the possibility to explore

the connection between these variables further, since, as mentioned by Tang et al. (2017), smartphone users may prefer a reward that is closer in time given the immediateness of access to information and entertainment provided by mobile services, thus generating a behaviour pattern that is more sensitive to the swiftness with which these kinds of experiences are attained. Results obtained, particularly for the first hypothesis, allow suggesting that studying the use of smartphones and its consequences on users' quality of life must go beyond usage time, since it is possible that the driving force behind influence may not be usage time as such, but motive of use or the context in which the use is taking place and its function (job-related, academic, entertainment), a thought that has been proposed in recent papers (Cho, 2020; Busch and McCarthy, 2021). Moreover, this study contributes to the literature on the use of smartphones from the perspective of behavioural economics in conjunction with traditional techniques such as screening tests as well as objective measures of use of smartphones and apps, finding a relationship between usage time and dependence on the device and a positive effect of this dependence on the average choice of the impulsive option.

5.3. Limitations and future research

Interpretation of the results must keep some limitations in mind. Firstly, and as reported similarly by Tang et al. (2017), the presentation of an immediate reward (SSR) took place through a fixed sequence, therefore caution must be exercised when comparing these results with those of studies applying a titrating sequence, although it can be considered that the two procedures have been used by researchers to establish delay discounting and it has been reported that there are no systematic differences in its estimation between these two techniques (Rodzon et al., 2011).

Secondly, the sample consisted of college students, thus, future studies could include participants with different age ranges to calculate possible differences in impulsiveness levels concerning usage time of smartphones and apps. Thirdly, although a small-N design perspective was applied, the sample size for future studies should be larger, including participants of different ages and occupations, which would give more depth to the results. Fourthly, the choice situations occurred in laboratory conditions, which may differ from users' daily conditions. Fifthly, future studies could incorporate qualitative measurements based on open-ended questions in order to collect data to allow interpretation of results in a broader way, especially when (as seen in this area of study) literature thus far has overwhelmingly followed quantitative techniques (cross-sectional surveys). Future studies could also apply different

designs to measure choice behaviours to provide evidence about the possible effect of variables associated with the use of smartphones on users' intertemporal choice.

6. Conclusion

The overall aim of this study was to investigate a possible relationship between the level of use of smartphones and apps and a pattern of impulsive choice, characterized by favouring positive yet immediate consequences. Regarding this possible relationship, the usage time of smartphones or apps was found to have no effect on the users' intertemporal choice. On the other hand, a correlation was found between the total usage time of the smartphone and the WhatsApp and Facebook apps and the smartphone dependence level obtained with the SPAI-S score. This result provides preliminary evidence as to what type of apps can be related to higher levels of dependency from objective measures of time of use. Additionally, smartphone dependence had a significant and positive effect on the average of impulsive choice behaviour (SSR). This is relevant because this relationship is established through data obtained in a choice test, unlike previous studies that applied screening scales to determine impulsiveness as a personality trait. This opens the possibility to continue exploring the relationship between the use of mobile services and a choice pattern based on the concept of temporal discounting from the perspective of behavioural economics. Finally, the study of the relationship between the use of smartphones and other choice behaviours must include contextual factors and different types of uses and benefits for consumers derived from mobile apps.

Declarations

Author contribution statement

O. Robayo-Pinzon: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

G. R. Foxall: Conceived and designed the experiments; Analyzed and interpreted the data.

L. A. Montoya-Restrepo: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

S. Rojas-Berrío: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

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