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Use of smartphone apps for mobile communication and social digital pressure: A longitudinal panel study

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ABSTRACT

The rapid growth in the availability of communication apps with mobile connectivity has contributed to an overabundant digital environment in the daily lives of individuals. Users of these communication apps are at risk of experiencing social digital pressure (SDP), which has been shown to be an important antecedent of smartphone addiction. These ideas, advanced by communication theorists, have not yet found clear empirical support. In this study, we analyze the actual use of communication apps among 1331 users from a nationally representative sample and relate it empirically to both SDP levels and their evolution over 18 months. Analyses of variance and latent growth modeling results showed that 1) SDP was significantly related to extensive use of communication apps and 2) among users with extensive use of communication apps, SDP increased significantly over time. Thus, smartphone use is associated with elevated SDP levels that tend to increase over time.

The number of studies exploring the possible effect exerted by the escalating use of information and communication technologies (ICTs) in society on the psychological and psychosocial well-being of users has increased considerably in recent years (Elhai et al., 2017; Huang, 2010; Kaur et al., 2021; Munzel et al., 2018; Kim et al., 2009; Kraut et al., 1998; Orben and Przybylski, 2019; Schemer et al., 2021; Vahedi and Saiphoo, 2018). The use of these ICTs has been explained in terms of individual variables (Busch and McCarthy, 2021; Marengo et al., 2020; Stachl et al., 2017; Yayan et al., 2019) but has also been related to the growing availability of digital applications and platforms designed for human communication (Gui and Büchi, 2021; Halfmann and Rieger, 2019). In fact, some authors have warned that in the last few years, this digital overabundance of apps for human communication has led to the emergence of a sort of tyranny of connectivity (mainly mobile) in our society (Kushlev et al., 2019; Vanden Abeele, 2021; Vanden Abeele et al., 2018): our connectivity is fully traceable and visible to other users (e.g., social relations, groups, institutions, etc.) who can demand complete availability and rapid responses to their online communications. In this social context of digital overabundance, the tendency of users to be connected and socially responsive can lead to an excessive use of ICT devices, which, in certain cases, can be the basis for developing a technological addiction (Büchi et al., 2019; Gui and Büchi, 2021; Herrero et al., 2021a). The focus of the present study is the analysis of the relationship of this extensive use to social digital pressure (SDP), which is a key element that has been associated with users' psychological wellbeing (Gui and Büchi, 2021) and ICT addiction (e.g., to smartphones) (Herrero et al., 2021a).

1. Empirical research on the effects of communication app usage and social digital pressure

When a smartphone user is socially responsive, he or she is likely to conform to normative expectations about availability and reciprocity in his or her communication process with the social world (groups and individuals) (Busch and McCarthy, 2021; Ling, 2016; Taylor and Bazarova, 2021). In the context of digital overabundance, however, demands can be so overwhelming that this social responsiveness may result in a kind of social pressure to be constantly attentive and respond promptly in the communicative process (Gui and Büchi, 2021; Halfmann and Rieger, 2019). This combination of pressure to comply with normative demands, social responsiveness and digital overabundance is a breeding ground for the emergence of SDP on users. SDP refers to the ability to function digitally and manage the everyday challenges of digital communication (Busch and McCarthy, 2021), which includes expectations regarding online responsiveness, skills, and social presence (Gui and Büchi, 2021).

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SDP may compromise the user's ability to disconnect and regain control over the device (Vanden Abeele, 2021), which might negatively relate to his or her digital well-being. Because we now live in a context of ubiquitous connectivity in which people have become individually addressable, users need to negotiate how to respond to the demands and expectations derived from this addressability (Vanden Abeele et al., 2018). While some users are able to maintain a balance between these demands derived from pervasive connectivity and their right to be disconnected (digital well-being), others may experience strong pressure to remain connected and socially responsive to the detriment of their ability to disconnect voluntarily (digital stress) (Dadischeck, 2021; Dennis, 2021; Steele et al., 2020).

While empirical research in this field initially suggested that SDP does appear to be related to increased use of internet communication apps (Büchi et al., 2019; Gui and Büchi, 2021), these investigations have some methodological weaknesses that need to be addressed. First, the measures used, based on self-reports, may incorporate problems of recall or social desirability. Studies show that self-reported time of use has systematic biases compared to actual time of use (see Parry et al., 2021 for a review and meta-analysis). In addition, when users are asked about potentially sensitive questions (how much time they spend connected to communication applications), there is a risk of obtaining systematically downward biased answers due to social desirability, as the most recent research has shown (Herrero et al., 2021b; Herrero et al., 2019d). Second, these self-reported measures of the use of mobile connectivity communication apps typically refer to whether the apps have been used over a period of time (e.g., three months). As a result, such measures do not allow us to distinguish use from frequency or intensity of use (Kobayashi and Boase, 2012; Parry et al., 2021). Because finding a direct empirical relationship between SDP and the frequency of the use of communication applications for mobile connectivity is likely, the availability of measurements that truly capture the actual use of these communication applications is key, as this may affect the size of the effects found (Jones-Jang et al., 2020). Third, these empirical contributions have also been the result of correlational studies that do not allow us to analyze to what extent the extensive use of communication apps is related to the increase in SDP over time. Therefore, the results obtained thus far do not shed light directly on the dynamics established between the extensive use of communication apps and SDP. This is undoubtedly a key issue that research in this field should continue to address.

2. The present study

The empirical studies reviewed suggest that the overuse of communication applications for mobile connectivity could be linked to users' SDP experiences (Büchi et al., 2019; Gui and Büchi, 2021). The development of these lines of research is also in accordance with recent contributions of digital communication theorists (Büchi, 2020; Dadischeck, 2021; Vanden Abeele, 2021), who emphasize the study of both individual and cultural aspects for understanding technological dependence and/or addiction. It is at this point that SDP can play a fundamental role since it reflects the characteristics of the social and cultural context in which the use of the device occurs. This social and cultural space may pressure the user into unrestrained and excessive use of communication applications for mobile connectivity, and firms generally use this information to personalize consumers' online navigation and improve their online experience (Cloarec, 2020). This is fundamentally a consequence of a culture of social responsiveness, not of a user's addiction-prone personal characteristics (Büchi et al., 2019; Ling, 2016), via its effect on SDP (Herrero et al., 2021a). Mobile connectivity communication apps show a very strong penetration in the general population, so understanding the link between SDP and the use of these apps is of utmost importance for monitoring the potential threats derived from digital overabundance in our societies.

In the present study, we deepened the empirical analysis of the relationship between SDP and smartphone usage in communication using an innovative approach. We studied logged data of smartphone use (Deng et al., 2019; Verkasalo et al., 2010), and we focused on the evolution of SDP using a longitudinal design with temporal panels. Our starting hypothesis was that users of smartphones with extensive use of communication applications will report higher levels of SDP compared to users with marginal use of these apps (1) and that, due to a sharp increase in the availability of communication apps for mobile connectivity, an increase in SDP will be observed over time in the general population (2). This hypothesis thus combines two ideas that researchers have been emphasizing in recent years: a) the increased use of communication apps may generate SDP (Gui and Büchi, 2021; Herrero et al., 2021a, 2021b), and b) the widespread development of mobile connectivity and apps for human communication will generate higher rates of SDP in the population (Büchi et al., 2019; Halfmann and Rieger, 2019; Williams, 2018).

This strategy aimed to refine the study of smartphone use beyond participants self-reporting whether they use certain communication apps. This approach allowed us to overcome potential limitations, such as the existence of possible recall biases and social desirability in self-reports of usage, thus providing a more accurate picture of the actual levels of usage (Sewall et al., 2020; Verkasalo et al., 2010). It also facilitated the study of the evolution of SDP in relation to these patterns of communication app usage. Finally, to support the generalization of the results, we studied these empirical relationships in a representative national sample of smartphone users.

Therefore, our research incorporated actual usage data with self-reported data about SDP in a longitudinal research design with temporal panels among a nationally representative sample of users.

3. Method

3.1. Participants

Data from the Cybersecurity and Confidence in Spanish Households National Survey (CCSHNS) conducted by the National Observatory of Telecommunications and Information Society were used for this study. The CCSHNS is a nationally representative survey of Spanish internet users on cybersecurity conducted every six months (see Herrero et al., 2021b). Data from three time panels obtained between the second half of 2019 and the first half of 2020 were used for this study. Each panel of the study was conducted on a representative sample of the population of internet users aged 18 to 75. For this study, 1331 participants had complete data on the study variables during the 18-month follow-up.

The CCSHNS survey regularly obtains information from two types of sources: participants' self-report responses and information obtained remotely from their smartphones after informed consent. Self-reported information includes sociodemographic characterization, usage habits, and other psychological and psychosocial variables, such as personality, psychological distress, psychosocial well-being, extensive smartphone use and addiction, and social digital pressure (SDP) (see Herrero et al., 2021a, 2021b). The information obtained remotely from the terminals (i.e., smartphones) provides a record of security vulnerabilities, malware infections, and application usage data during the scanning period (Herrero et al., 2019a).

Several studies have already used this database to delve into the relationship between addiction and various psychological and psychosocial variables and the scanned data (Herrero et al., 2021a, 2021b; Solano et al., 2021). In this study, we focus on the scanned record of app use and its relationship with social digital pressure.

3.2. Variables and scales

3.2.1. Logged data

At the beginning of Panel 3 (T3), users voluntarily downloaded and installed an application that remotely allowed investigators to obtain information on the status of the terminal. This application made it possible to record potential vulnerabilities in the security of the terminals as well as the usage patterns of a set of applications. The software detected the amount of time (in milliseconds, which were later converted to hours) that a given application had been active on the terminal during a given period of time. The software scanned twice for the type of usage performed from the installation to the time of the first scan (one) and from the last scan to the second scan (two) during the semester. The sum of the days scanned on these two occasions was the total number of scanning days (mean = 128.89, S.D. = 54.80). This total number of scanning days was used to estimate the usage time in hours of each application per day (dividing total recorded usage by the number of scanning days).

Although the software detected a large number of apps installed and active on the terminal, for this study, we substantially reduced this number and focused on those applications most commonly used by Android users. The reason for this is twofold: on the one hand, many apps registered a practically residual use, and on the other hand, many applications did not register their presence on most of the terminals. For these reasons, in the present study, we limit the analysis to the following applications: Twitter, Mail, YouTube, Spotify, Telegram, Microsoft Office, Phone calls, Chrome, WhatsApp, Facebook, Instagram, Amazon, Wallapop, Zoom and Skype.

3.2.2. Averaged total use of applications (h/day)

For the calculation of averaged total application usage, the usage of each application was summed and divided by the number of applications (16) (mean = 0.19, S.D. = 0.40). Table 1 presents the descriptive data for each of the applications analyzed in this study.

3.2.3. Averaged total use of communication applications (h/day)

The average use of the following communication applications was calculated: Twitter, Mail, Telegram, Phone calls, WhatsApp, Facebook, Instagram, Zoom, and Skype. For the calculation of averaged total communication application use, the use of each application was summed and divided by the number of communication applications (9) (mean = 0.11, S.D. = 0.27). Table 1 presents the descriptive data for each of the applications analyzed in this study.

According to the data shown in Table 1, the following stand out among the most extensively used apps: WhatsApp (M = 0.78) and Chrome (M = 0.74). Half of the applications analyzed were used by most of the participants at least one time (mode): YouTube, Microsoft Office, Phone Calls, Chrome, WhatsApp, Facebook, Instagram, and Amazon. The percentage of communication app usage as a function of total usage was 58 % (0.11/0.19 = 0.58), suggesting that in the terminals scanned, more than half of the recorded usage corresponded to communication apps.

Table 1
Logged data of the six-month average daily use of 16 smartphone apps for mobile connectivity: total sample and two groups of nonfrequent and frequent users averaged daily use (in hours).

App.	Total sample (N = 1331)	Nonfrequent use (n = 441)	Frequent use (n = 890)	p
Twitter	0.09 (0.41)	0.02 (0.17)	0.12 (0.48)	<.001
Mail	0.04 (0.29)	0.01 (0.06)	0.05 (0.35)	.011
Telegram	0.05 (0.29)	0.01 (0.07)	0.07 (0.34)	<.001
Phone calls	0.14 (0.43)	0.05 (0.26)	0.19 (0.49)	<.001
WhatsApp	0.78 (2.04)	0.22 (0.69)	1.06 (2.38)	<.001
Facebook	0.43 (1.42)	0.13 (0.62)	0.59 (1.67)	<.001
Instagram	0.36 (1.60)	0.04 (0.22)	0.53 (1.93)	<.001
Zoom	0.01 (0.01)	0.00 (0.00)	0.01 (0.08)	.021
Skype	0.01 (0.04)	0.00 (0.01)	0.01 (0.05)	.046
YouTube	0.28 (0.95)	0.09 (0.10)	0.37 (1.13)	<.001
Netflix	0.06 (0.61)	0.01 (0.08)	0.09 (0.75)	.016
Spotify	0.01 (0.08)	0.01 (0.01)	0.02 (0.10)	<.001
Microsoft	0.06 (0.30)	0.02 (0.18)	0.08 (0.34)	<.001
Chrome	0.74 (2.02)	0.32 (1.15)	0.94 (2.31)	<.001
Amazon	0.09 (0.38)	0.03 (0.20)	0.12 (0.45)	<.001
Wallapop	0.04 (0.22)	0.01 (0.07)	0.05 (0.27)	<.001
Averaged use: All apps.	0.19 (0.40)	0.06 (0.15)	0.26 (0.46)	<.001
Averaged use: Communication apps.	0.11 (0.27)	0.03 (0.09)	0.16 (0.31)	<.001

3.2.4. Social digital pressure

We used the Gui and Büchi (2021) three-item Social Digital Pressure Scale. It measures the following three indicators: (a) social pressure to respond quickly to communication (*in my everyday life, people expect that I reply quickly to messages*), (b) social expectations of digital skills (*in my everyday life, people expect that I am capable of using various internet applications*), and (c) expectations of online social presence (*in my everyday life, people expect me to be active on social networking sites*). Category responses ranged from 1 = completely disagree to 5 = completely agree. Items were summed and averaged. SDP was evaluated in three time panels (T1, mean = 3.47, S.D. = 0.80; T2, mean = 3.49, S.D. = 0.82; T3, mean = 3.51, S.D. = 0.78). Cronbach's α ranged from 0.75 to 0.77, while McDonald's ω ranged from 0.75 to 0.78.

SDP was positively and significantly correlated with both total app usage ($r = 0.08$, $p < .001$) and communication app usage ($r = 0.09$, $p < .001$) at T3.

3.2.5. Sociodemographic variables

Sex (male 50.7 %, female 49.3 %); age (M = 44.88, S.D. = 1.20); educational background [highest educational level attainment, 1 = elementary (0.8 %), 2 = secondary (46.1 %) and 3 = university studies (53.1 %) (M = 2.52, S.D. = 0.51)]; and size of locality [from 1–<10,000 to 6–>500,000 inhabitants (M = 3.83, S.D. = 1.79)].

3.3. Analytical strategy

First, participants were classified according to their application usage profile using a two-stage cluster analysis. This procedure is appropriate when the optimal number of clusters that best describes the sample is not known a priori. Using two-stage cluster analysis, we first identified the optimal number of clusters that best described the variability of app use among participants. After identifying the optimal number of groups, we proceeded to use the two-stage cluster analysis to classify participants into groups following the criterion of maximizing between-group variability and minimizing within-group variability.

Once the optimal number of clusters was identified, the evolution of SDP in each cluster was evaluated through the analysis of latent growth models (LGM) for the multiple groups technique. This phase of the study aimed to identify different SDP trajectories over time in each of the clusters.

The basic assumption behind LGM is that there is an underlying, unobserved (i.e., latent) growth process responsible for the pattern of change observed in repeated measures - at least three measures - of a variable over time. The analysis of growth curves provides information on two parameters that allow us to describe the evolution of a variable over time: the initial level or intercept and the growth rate or slope. The intercept indicates the average level of the variable at the beginning of the study, and the slope provides information about the type of evolution. A significant and negative slope indicates a decrease in mean levels over time, while a significant and positive slope indicates a mean increase over time. A nonsignificant slope (not different from zero) indicates zero growth over time (Herrero et al., 2019a). Using the intercept and slope of each individual, LGM is able to identify the trajectories of each individual in a sample.

The sample mean intercept and slope characterize the mean trajectory of a population, while their variances are used to identify potential heterogeneities in the trajectories. A significant variance of the intercept suggests that not all participants start the study with the same levels on the variable, and a significant variance of the slope suggests that the detected trajectories are not homogeneous for the whole sample. In the latter case, it may indicate that not all participants evolve at the same rate (increasing or decreasing) or that they have different trajectories (some grow, others decrease and others remain the same) (Grimm and Ram, 2018).

In the third and final phase of the analyses, we used multiple-sample LGM to test whether the initial levels and evolution of SDP were similar or different across groups using version 8.3 of MPLUS software (Muthén and Muthén, 1998–2017).

Multiple-sample LGM has the potential to test for similarities and differences in developmental processes across different populations (Duncan and Duncan, 2009). In our specific case, we applied multiple sample LGM to estimate and compare SDP trajectories over time among participants with different frequencies of app use.

4. Results

First, a two-stage cluster analysis was performed to identify the optimal number of groups that best described the use of each of the 16 apps studied. Two groups were identified, whose average use per app is presented in Table 1. Participants in Group 1 ($n = 441$) showed a very low average use in all apps. Except for Chrome ($M = 0.32$, $S.D. = 1.15$) and WhatsApp ($M = 0.22$, $S.D. = 0.69$), the overall device usage was residual. Group 2 ($n = 890$) registered a more extensive use in most of the apps, mainly in the average use of WhatsApp ($M = 1.06$, $S.D. = 2.38$), Chrome ($M = 0.94$, $S.D. = 2.31$), Facebook ($M = 0.59$, $S.D. = 1.67$), and Instagram ($M = 0.53$, $S.D. = 1.93$). The sociodemographic characterization of each group was as follows. Younger participants (F 1, $1329 = 32.31$, $p < .001$; Group 1, $M = 47.42$, $S.D. = 11.55$, Group 2, $M = 43.62$, $S.D. = 11.44$), and female participants ($\chi2 = 6.18$, $df = 1$, $p = .13$, Cramer's $v = 0.07$) tended to belong to Group 2. The groups did not differ significantly in educational level ($F1,129 = 0.64$, ns) or size of locality ($F1,129 = 0.13$, ns).

Multivariate analysis of variance results showed that the average use of each of the apps was significantly lower in Group 1 than in Group 2 (Wilk's $\Lambda = 16.54$, $p < .001$). Univariate analysis of variance showed that this statistical significance was $p < .001$ for all apps except for Skype ($p = .046$), Mail ($p = .011$), Netflix ($p = .016$) and Zoom ($p = .021$), which also showed statistically significant differences between the two groups. Overall, therefore, participants in Group 1 used the various apps on average much less frequently than participants in Group 2. For both total and communication app usage, Group 2 showed significantly higher levels than Group 1. An inspection of the internal consistency indices for Groups 1 and 2 of the SDP scale confirmed that these were in the ranges observed for the overall sample in the three time periods: Cronbach's α ranged from 0.75 to 0.77, while McDonald's ω ranged from 0.75 to 0.78.

Groups 1 and 2 also differed statistically in their average SDP levels (Wilk's $\Lambda = 8.22$, $p < .001$), as revealed by multivariate analysis of variance. Univariate analyses of variance showed that SDP at T1 (F 1, $1329 = 11.27$, $p < .001$; Group 1, $M = 3.37$, $S.D. = 0.81$, Group 2, $M = 3.52$, $S.D. = 0.79$), T2 (F 1, $1329 = 13.59$, $p < .001$; Group 1, $M = 3.38$, $S.D. = 0.84$, Group 2, $M = 3.55$, $S.D. = 0.80$), and T3 (F 1, $1329 = 20.13$, $p < .001$; Group 1, $M = 3.39$, $S.D. = 0.78$, Group 2, $M = 3.58$, $S.D. = 0.77$) were significantly lower in Group 1 than in Group 2. In fact, while SDP maintained a very slight increase in Group 1 over time (from 3.37 to 3.39), its growth rate appeared to be faster in Group 2 (from 3.52 to 3.58). Although this suggested a different evolution of SDP in each group, in the last phase of the analyses, we checked this by using latent growth models (LGMs) for multiple groups.

Using the LGM technique for multiple groups, we simultaneously estimated a growth model for Group 1 and Group 2. In this model, both intercepts and slopes were held different in both groups: the initial rate and evolution of SDP throughout the study was different for both groups. The fit of this model was good ($\chi2 = 0.16$, $d.f. = 2$, $p = .99$; $CFI = 1.00$; $RMSEA = 0.00$, 95 % C.I. 0.00, 0.00). This model seemed to perform better than the model that maintained equality between intercepts and slopes across groups: the SDP for both groups did not differ either in their initial rates or in their evolution. ($\chi2 = 27.45$, $d.f. = 6$, $p < .001$; $CFI = 0.96$; $RMSEA = 0.07$, 95 % C.I. 0.04, 0.10). The likelihood ratio test (LRT) for nested models showed that the model imposing equalities of intercept and slope across groups was statistically worse ($\Delta\chi2 = 23.85$, $\Delta df = 4$, $p < .001$) than the model with different intercepts and slopes in both groups. The model with different intercepts and slopes across groups was retained for further analysis.

Table 2 shows the unstandardized results of the final LGM. In this model, Group 1 had an initial SDP value of 3.37 ($S.E. = 0.04$, $p < .001$) and a slope of 0.01 ($S.E. = 0.02$, ns), which was not significant. For Group 2, an initial SDP value of 3.52 ($S.E. = 0.03$, $p < .001$) and a statistically significant slope of 0.03 ($S.E. = 0.01$, $p < .05$) were observed. Accordingly, the Group 1 participants started the study with lower SDP levels that tended to increase marginally during the study. The Group 2 participants, on the other hand, started the study with higher SDP levels that actually increased gradually and significantly during the study (see Fig. 1). The intercept and slope variances inform us of the between-subject variability. Initial SDP levels at T1 significantly varied in both groups (var. intercept Group $1 = 0.38$, $S.E. = 0.07$, $p < .001$; var. intercept Group $2 = 0.31$, $S.E. = 0.04$, $p < .001$). Not all individuals in Groups 1 and 2 started the study with the same SDP levels.

Growth rates did not vary within Group 1 (var. slope $= 0.01$, $S.E. = 0.03$, $p = .78$) but significantly varied among the subjects in Group 2 (var. slope $= 0.04$, $S.E. = 0.02$, $p < .05$). Thus, not all members of Group 2 started the study with the same SDP levels, nor did SDP grow at the same rate among them.

The summary of LGM parameters indicates that a) both groups differed in their initial SDP levels; b) Group 1 subjects consistently and homogeneously maintained their SDP levels throughout the study; and c) Group 2 subjects showed positive mean growth, which nevertheless varied significantly among the subjects. The smartphones of users in Group 1 were characterized by lower overall usage and lower use of communication apps. In general, users of these devices tended to be older and have a higher proportion of males. Users in Group 1 showed lower levels of SDP and these tended to remain stable during the study. The smartphones of users in Group 2, on the other hand, registered not only a higher range of active apps but also a higher overall use of these apps, including communication apps. Users in Group 2 reported higher levels of SDP at baseline and a significant increase in SDP throughout the study.

These results showed that 1) extensive smartphone use was significantly related to higher SDP levels; 2) when the level of smartphone use was low and even residual, SDP levels tended to remain relatively constant over time; and 3) when the level of smartphone use was high, including extensive use of communication apps, not only was SDP higher but it seemed to increase significantly over time. Smartphone use, therefore, is associated with high SDP levels that tend to increase over time.

Table 2
SDP unstandardized parameter estimates of latent growth analysis for two groups of nonfrequent and frequent users.

	Group 1 (nonfrequent)		Group 2 (frequent)	
	Estimate	S.E.	Estimate	S.E.
Mean intercept	3.37***	0.04	3.52***	0.03
Mean slope	0.01	0.02	0.03*	0.01
Variance intercept	0.38***	0.07	0.31***	0.04
Variance slope	0.01	0.03	0.04*	0.02

*** $p < .001$.
* $p < .05$.

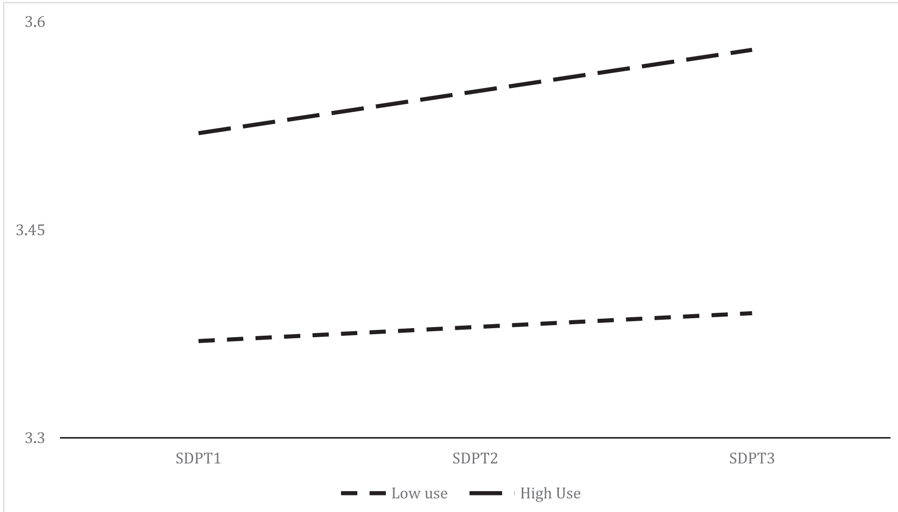

Fig. 1. Evolution of SDP across groups of nonfrequent/low use (n = 440) and frequent/high use (n = 891) users of communication apps for mobile connectivity. Note: SDPT1-SDPT3 represent social digital pressure from T1 to T3.

5. Discussion

The last few years have witnessed rapid growth in the availability of mobile connectivity communication apps, which has contributed to generating an overabundant digital environment in individuals' daily lives (Vanden Abeele et al., 2018). Users of these communication apps are at risk of developing SDP, which has been shown to be an important antecedent of poor psychological wellbeing (Büchi et al., 2019; Gui and Büchi, 2021) and smartphone addiction (Herrero et al., 2021a, 2021b, 2021c). In this study, we analyze the actual use of communication apps among 1331 users from a nationally representative sample and relate it empirically to both the levels of SDP and its evolution over 18 months. Our starting hypothesis was that more frequent use of mobile connectivity communication apps would be associated with higher SDP. Furthermore, due to the increased availability of these types of apps (Williams, 2018), we predicted that there would be a trend toward an increase in SDP in the general population.

The results of our research provide empirical support for our starting hypothesis: the use of mobile connectivity communication apps is positively and significantly related to SDP. In addition, there is a trend toward an increase in SDP in the population, although this increase is only significant for users with extensive use of communication apps.

Other researchers have also empirically linked SDP to the use of apps for communication (Büchi et al., 2019; Gui and Büchi, 2021). However, these previous investigations have been conducted with self-reported measures of whether these applications had been used in the last few months. Our research adds to these previous studies by improving the measurements of communication app use. The literature in this field has pointed out that self-reported and logged use correlate weakly or moderately at best, and a number of potential biases have been noted that could account for this weak relationship (see Parry et al., 2021 for a systematic review and meta-analysis of studies).

According to the results of our study, moreover, there was a general trend among study participants of a steady increase in SDP over time, although this trend was more pronounced among users with more frequent use of communication apps. Most of the 1331 users who took part in the study (67 %) were identified as frequent users of communication apps. This in itself indicates the widespread use of these types of apps in the general population. In addition, a closer inspection of the remaining participants identified as nonfrequent users revealed a residual use with the exception of instant messaging applications (WhatsApp) and web browsers (Chrome) that in any case did not reach an average use of 15 min a day.

These results suggest that contexts characterized by a high frequency of digital communication could eventually exert increasing social pressure on users, resulting in higher rates of connectivity and, probably, device-dependent use. Thus, these digital contexts directly affect users' need for mobile connectivity, which takes away their autonomy to achieve a healthy balance between the time they spend online and the time they choose to disconnect. This imbalance has been linked to poor digital well-being—an outcome of social relationships and interactions on social networking sites—(Dadischeck, 2021; Munzel et al., 2018; Vanden Abeele, 2021) and an increased likelihood of developing addictive behavior with smartphones (Herrero et al., 2021a).

Our results indicate that a) mobile communication applications can generate SDP and b) there is a tendency in the general population to increase SDP levels over time. Therefore, the ubiquity of mobile connectivity and the availability of apps for human communication anticipate an increase in SDP in the general population over time.

Moreover, this increase in SDP becomes even more pronounced with more extensive use of these communication apps for mobile connectivity. Indeed, this anticipated increase in SDP, both for the general population and more specifically for users with extensive use of these apps, may negatively affect users' digital well-being.

If we combine these results with the evolution of devices, applications and platforms for human communication in digital environments, potential signs of concern are detected. Important aspects of the digital industry, such as the rise of addictive application designs specifically aimed at retaining maximum user attention (Bhargava and Velasquez, 2021; Williams, 2018), envision an evolution in digital human communication environments toward a greater ability to generate SDP on users. In addition, SDP has been linked to a relative lack of psychological and psychosocial resources, such as lower social support or higher rates of smartphone addiction (Ihm, 2018; Kushlev et al., 2019; Herrero et al., 2019a, 2019b, 2019c; Herrero et al., 2021c; Lapierre and Zhao, 2021; Yayan et al., 2019), something that undoubtedly increases the vulnerability of users immersed in rampant mobile connectivity. From this point of view, the user would be ill prepared to cope with these new threats from corporate interests.

Perhaps it would not be disproportionate to consider whether in this case it would be suitable for policy-makers to promote certain regulations to protect those who use communication apps for mobile connectivity (Simons and Ghosh, 2020; Williams, 2018), as with other areas such as health apps (Shuren et al., 2018). Some initial guidance on this topic might be found in Williams's (2018) analysis of the attention economy, where advertising, design, responsibility or transparency are key issues to demand from a digital industry that is minimally concerned about the end user. From this point of view, social responsibility and industry self-regulation are key elements that can help mitigate the negative effects of the digitalization of our societies (Dennis, 2021; Floridi, 2021; Kozyreva et al., 2020).

Finally, it should be pointed out that our findings do not necessarily suggest that the use of communication apps should be demonized. As other authors have pointed out, communication in digital environments based on mobile connectivity provides very positive returns for the users (Vanden Abeele, 2021; Williams, 2018). It allows them to connect with their loved ones, obtain immediate gratification in their communications with people and groups, access social relationships with common interests and motivations, etc. When could this permanent availability become a cause for concern? The most recent findings in this field provide an initial answer: concern should begin when digital well-being starts to be compromised. That is, there is cause for concern when the user's ability to choose between staying connected or disconnecting begins to be threatened.

5.1. Strengths and limitations

The present research has some strengths that should be noted as well as some potential limitations. A first strength lies in the research design, which combines logged and self-reported data. By using logged data from remote scanning of the terminals (i.e., smartphones), more precise and objective measurements of the use of each app are obtained. This has additional advantages, such as mitigating the potential effect of social desirability or recall problems associated with such usage (Vanden Abeele et al., 2013). Moreover, the average usage times were logged over a broad six-month period, which we understand provides a fairly accurate estimate of usage habits with the device. Compared to other approaches, such as measuring logged usage during the last week or month, such a long period of six months allows us to find regularities in the use of communication apps that are unaffected by the occurrence of peak or off-peak periods. This strategy partially attenuates the effects that short periods of intense or extremely low use may have on the average logged usage variable score. In addition, as these data are derived from different sources (logged data of use and participant self-reported SDP), potential biases such as common method variance (Sewall et al., 2020; Parry et al., 2021) are controlled for. Second, this research uses nationally representative data on smartphone users. Typical in this area of study is the analysis of correlational data, often with convenience samples (e.g., university students). The results of these studies do not allow the incorporation of the time variable in their explanations, which limits the type of inferences supported by the data. In addition, representative samples of the general population are not usually used, which limits the generalizability of the results. Third, this research incorporates a longitudinal design, which allows us to analyze the evolution of SDP over time. The use of a time panel design allowed us to analyze the evolution of SDP in our study, an aspect that has been neglected in research until now. This, together with the robustness of the statistical techniques applied (LGM), allows us to be confident in the generalizability of the study results.

For potential limitations, the longitudinal design with three measurements (panels) every six months could have conditioned the evolution found for SDP. Thus, perhaps a period of six months is an insufficient interval to observe significant changes in some users' SDP, especially those who started with lower levels at the beginning of the study. Specifically, among users with low levels of use of communication apps, the model also detected an increase in SDP over time, although this increase was not statistically significant. It is possible that in users with a very low usage profile and with low SDP levels, six months may not be an adequate interval to capture substantial changes. This could be because the smartphones of these users registered a residual use of communication apps and that at these levels of residual use, changes in SDP are not generated sufficiently to be detected by statistical procedures. A second potential limitation lies in the fact that we only evaluated the evolution of self-reported data (SDP) but not of logged data. Therefore, it is not possible to interpret the results in terms of usage trajectories and SDP trajectories. With due caution, however, the results did allow us to link extensive use with SDP growth over time, which could serve as a basis for further research that also incorporates the evolution of logged use. Finally, the logged usage data obtained in this study (first half of 2020) may incorporate some of the overuse of apps associated with the lockdown caused by the COVID pandemic. This may have somewhat inflated the use of such apps for mobile communication in this specific period. We consider, however, that this circumstance has not significantly affected the main results of the study. The fact that there may have been a peak in app usage during the lockdown would have initially affected most users. Furthermore, since the aim of the study was to analyze the association between SDP and the use of apps for mobile communication, these generalized increases in use in the population do not seem to constitute a threat to the internal validity of the study. Thus, even incorporating the more extensive use of apps during lockdown, the relationship between this use and the evolution of SDP is clear: higher levels of use were associated with an increase in SDP over time.

6. Conclusions

In the context of the rapidly growing availability of communication apps for mobile connectivity, an increase in SDP is likely. Users are permanently connected, and their availability is traceable by other users, who can make demands on their responsiveness in the communication process. As a consequence, users may be forced to be permanently attentive to their communications with other users. This can generate high levels of SDP, which directly affects their ability to decide when to stay connected and when to disconnect (digital well-being).

Both the designs of these apps, which provide multiple ways for users to know the status of their communication, and the eminently social and responsive nature of the users become elements that exert a notable pressure on individuals. To some extent, this is incompatible with their digital and subjective well-being and could be the basis for explaining some negative consequences of the extensive use of these apps, such as poor mental health, addictive behavior, or psychosocial adjustment problems.

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CRediT authorship contribution statement

Juan Herrero: Supervision, Conceptualization, Methodology, Validation, Writing – review & editing, Writing – original draft. **Francisco J. Rodríguez:** Methodology, Validation, Writing – review & editing. **Alberto Urueña:** Investigation, Conceptualization, Methodology, Validation, Data curation, Writing – review & editing.

Conflicts of interest

The authors declare no conflict of interest.

Data availability

Data will be made available on request.

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