Experiential avoidance and excessive smartphone use: a Bayesian approach

Evitación experiencial y uso abusivo del smartphone: un enfoque bayesiano

Ana María Ruiz-Ruano*, María Dolores López-Salmerón**, Jorge L. Puga***

* UCAM Universidad Católica San Antonio de Murcia, Facultad de Ciencias Jurídicas y de la Empresa.
** Programa de Doctorado en Ciencias de la Salud. Universidad Católica de Murcia (UCAM).
*** UCAM Universidad Católica San Antonio de Murcia, Facultad de Ciencias de la Salud.

Abstract

The smartphone is a common tool in our everyday lives. However, recent research suggests that using the smartphone has both positive and negative consequences. Although there is no agreement on the concept or the term to label it, researchers and clinical practitioners are worried about the negative consequences derived from excessive smartphone usage. This study aims to analyse the relationship between smartphone addiction and experiential avoidance. A sample of 1176 participants (828 women) with ages ranging from 16 to 82 (*M* = 30.97; *SD* = 12.05) was used. The SAS-SV scale was used to measure smartphone addiction and the AAQ-II to assess experiential avoidance. To model the relationship between variables, Bayesian inference and Bayesian networks were used. The results show that experiential avoidance and social networks usage are directly related to smartphone addiction. Additionally, the data suggests that sex is playing a mediating role in the observed relationship between these variables. These results are useful for understanding healthy and pathological interaction with smartphones and could be helpful in orienting or planning future psychological interventions to treat smartphone addiction.

Keywords: Experiential avoidance; Smartphone; Addiction; Social networks; Bayesian inference.

Resumen

El uso del teléfono móvil se ha convertido en una actividad cotidiana en nuestro entorno más cercano. Dicho uso, según investigaciones recientes, tiene tanto aspectos positivos como negativos. Aunque hay controversia en cuanto a la denominación del fenómeno, se aprecia cierta preocupación por las consecuencias negativas que tiene el uso excesivo del teléfono móvil. Este estudio analiza la relación que se establece entre el uso abusivo del teléfono móvil y la evitación experiencial. Se utilizó una muestra compuesta por 1176 participantes (828 fueron mujeres) con edades comprendidas entre los 16 y los 82 años (*M* = 30.97; *DT* = 12.05). Se empleó la escala SAS-SV para valorar el uso problemático del móvil y el AAQ-II para la evitación experiencial. Para modelar la relación que se establece entre las variables se hizo uso de inferencia bayesiana y redes bayesianas. Los resultados muestran una relación directa entre el uso abusivo, la evitación experiencial y las redes sociales. Además, los datos sugieren que el sexo juega un papel mediador entre estas variables. Estos resultados son útiles para entender el uso saludable y patológico del teléfono móvil así como para orientar el tratamiento de los trastornos que pueden surgir de un mal uso de estos dispositivos.

Palabras clave: Evitación experiencial; Smartphone; Adicción; Redes sociales; Inferencia bayesiana.

The use of mobile phones in today's society has gone from being an isolated phenomenon to forming an almost essential activity in our lives (Odgers, 2018). Thus, authors such as Buchinger, Kriglstein, Brandt & Hlavacs (2011) qualify the mobile phone as an indispensable tool for current social and working life. Mobile phones, or so-called smartphones, offer a series of advantages such as allowing us to be more connected, promoting heightened group identity or being an easy means of communicating emotions (Tresáncoras, García-Oliva & Piqueras, 2017). Their use also has effects on the levels of autonomy and social prestige; it is a source for leisure and represents a way of promoting and establishing social relationships (Chóliz, Villanueva & Chóliz, 2009). Moreover, smartphones can be used as tools for interventions in certain pathologies and for data collection with applications focused on health (eg, Capon, Hall, Fry & Carter, 2016; Gustafson et al., 2014; Kuhn et al., 2017; Seoane & Álvarez, 2012). However, despite these positive aspects (Odgers, 2018), a wide range of studies indicate possible adverse effects that may arise from their misuse.

Nevertheless, there is no consensus on how the pernicious effects mobile phones have on health are described (Carbonell, Fúster, Chamorro & Oberst, 2012; Simó, Martínez, Ballester & Domínguez, 2017). Some authors advocate the terminology of excessive use (eg, Chóliz et al., 2009), problematic use (eg, Marín, Carballo & Coloma-Carmona, 2018; Pedrero-Pérez et al., 2018; Simó et al., 2017; Tresáncoras et al., 2017), maladaptive use (eg, Gil, del Valle, Oberst & Chamarro, 2015), or even addiction (eg, Carbonell et al., 2012). In any case, it seems that most studies attempt to locate this phenomenon within the so-called behavioural addictions. However, given how the diagnostic manuals deal with addictions, especially if we take the current DMS-5 (American Psychiatric Association [APA], 2013) as a reference point, to use the term mobile phone addiction may be both legitimate and questionable since there is a lack of consensus on the subject (Simó et al., 2017).

In any case, there are certain studies that emphasize the harmful consequences of such excessive or problematic use of mobile phones, pointing out physical and psychological consequences (stress or anxiety) in social, family, school or work contexts (eg, Babín, 2009; Echeburúa & Corral, 2010; Hardell, Carlbert & Hansson, 2011; Klawer et al., 2014; Lee, Kang & Shin, 2015; Marín et al., 2018; Zarghami, Khalilian, Setareh & Salehpour, 2015). Within these negative consequences, the emergence of new maladaptive behaviours linked to mobile phone use has also been described (eg, Bragazzi & Puente, 2014; Gil et al., 2015; Karadağ et al., 2015; Krasnova, Abramova, Notter & Baumann, 2016; McDaniel & Coyne, 2016; Mendoza & Cuñarro, 2016; Roberts & David, 2016; Rodríguez, 2015; Wang, Xie, Wang, Wang & Lei, 2017).

From a theoretical point of view, it appears that women may be more prone to problematic use of smartphones (Veissière & Stendel, 2018), given their greater tendency towards prosocial behaviour compared to men. Similarly, Karadağ et al. (2015) point out that women make more use of smartphones than men because of their greater desire to be liked and to share their experiences. In addition, there is a series of studies showing that women spend more time using smartphones, instant messaging and social networks (eg, Chóliz, 2012; Chóliz et al., 2009; De-Sola, Rodríguez & Rubio, 2016; Gil et al., 2015; Pedrero-Pérez et al., 2018, Tresáncoras et al., 2017). Another relevant aspect found in some of these studies is that, in some cases, women state that the use of mobile phones helps them deal with unhappy moods (Chóliz et al., 2009; De-Sola et al., 2016), and even to "overcome boredom, deal with anxiety, or at times when they are sad or alone" (Chóliz et al., 2009, p.84). Finally, a review by Carbonell et al. (2012) of Spanish studies has found that women have more problems with the use of smartphones and also consider their use more problematic than do men.

Furthermore, the smartphone is one of the most, if not the most, frequently used tools to access social networks. Some studies show that social networks allow the development of positive aspects in people (eg, Pedrero, Rodríguez & Ruiz, 2012) and have transformed how social relationships are established (eg, Echeburúa & Corral, 2010; Orozco, 2015). However, despite the clear advantages provided by this type of technology, negative aspects are also linked to its use. For example, using social networks is considered a risk factor for excessive smartphone use (Deursen, Bolle, Hegner & Kommers, 2015; Griffiths, 2000; Zhitomirsky-Geffet & Blau, 2016), mental health problems or stress (Pedrero-Pérez et al., 2018) and especially for the adolescent population (Arab & Díaz, 2015; Chóliz et al., 2009; Tresáncoras et al., 2017).

From a psychological point of view, a possible explanation of the maladaptive use of the mobile phone in the field of social networks could be linked to the tendency to flee from aversive feelings provoked by non-virtual reality, especially in the case of women, as mentioned above (Carbonell et al., 2012; Chóliz et al., 2009). The concept of experiential avoidance or experiential avoidance disorder was coined precisely to allude to the maladaptive avoidance tendency linked to different mental disorders (Hayes, Wilson, Gifford, Follete & Strosahl, 1996). Within this paradigm, it is understood that certain psychological disorders are the result of a persistent pattern of maladaptive avoidance oriented towards negative internal events that produce chronic and generalized discomfort. It is understood that this pattern of dysfunctional functioning is based on verbal regulation processes (eg, Hayes, Brownstein, Zettle, Rosenfard & Korn, 1986; Hayes, Strosahl & Wilson, 1999; Hayes, Zettle & Rosenfarb, 1989; Wulfert, Greenway, Farkas, Hayes & Dougher, 1994), the person involved consequently experiencing social, personal and/or work-related limitations, which are transferred to different life contexts at a high personal cost (Wilson & Luciano, 2012).

In the context of addictions, it has been observed that the inappropriate or excessive use of chemical substances such as tobacco or alcohol is related to experiential avoidance. For example, in 2016, Levin et al. reported that people who drank excessively scored higher on experiential avoidance. Garey, Farris, Schmidt & Zvolensky (2016) suggest that smoking could be explained by an experiential avoidance mechanism conditioned by the usual stressors of everyday life. Furthermore, Watson, Heffner, McClure & Bricker (2017) provide evidence suggesting that smokers with high levels of social anxiety also present greater experiential avoidance. Bahrami & Asghari (2017), on the other hand, observed that experiential avoidance and inappropriate coping styles could explain therapeutic failure with methamphetamine-dependent patients. In addition, they concluded that the use of Acceptance and Commitment Therapy as a technique aimed at reducing experiential avoidance (Hayes et al., 1999) optimized the prospects for improvement for these patients. Buckner & Zvolensky (2014) also obtained evidence that a pattern of avoidance conditioned the social anxiety shown by cannabis users.

There are fewer studies that link experiential avoidance to behavioural addictions. In fact, the only disorder most directly linked to the idea of addiction is pathological gambling, and it is pointed out (criterion A.5 of DSM-5) that problematic behaviour appears as a consequence of unpleasant sensations such as restlessness, helplessness, depression or anxiety (APA, 2013). Moreover, internet gaming disorder is included in DSM-5 under conditions needing further study and if it were to be recognized as a disorder per se in the future, we would be dealing with the first disorder derived from the use of new technologies. According to the APA (2013), one of the diagnostic criteria for internet gaming disorder is directly related to experiential avoidance: criterion 8 states that pathological behaviour appears in order to "escape problems or alleviate negative emotions" (p. 795). A recent study by García-Oliva & Piqueras (2016) points out that there is a relationship between experiential avoidance and the use of information and communication technologies (ICTs). Specifically, they indicate that ICTs are used as a way of escaping from aversive internal stimuli.

Thus, given that experiential avoidance is associated with some addictive disorders (eg, Hayes et al., 1996), a link between this variable and excessive smartphone use could also be expected. Since social networks play a very important role in the use of mobile devices, as indicated above, it would not be surprising that the use of these tools for social interaction could be partially explained by high levels of experiential avoidance. In addition, one might also expect that problematic use of the mobile phone is related to sex since some authors link this variable to maladaptive smartphone use (eg, Chóliz, 2012; Choliz et al., 2009; Gil et al., 2015; Pedrero-Pérez et al., 2018; Tresáncoras et al., 2017). To study these hypothesised relationships between mobile phone abuse, preference for social network applications and experiential avoidance, we will use the automatic structural learning algorithms of Bayesian networks (eg, Nagarajan, Scutari & Lèbre, 2013; Ruiz-Ruano, 2015; Scutari, 2010). Bayesian networks are multivariate statistical tools that allow the probabilistic relationships established between a set of variables to be graphically modelled (Cowell, Dawid, Lauritzen & Spiegelhalter, 1999; Edwards, 1998; Puga, Krzywinski & Altman, 2015). Despite its potential usefulness, the automatic structural learning of Bayesian networks has been relatively little used in psychology compared to other applications used with this type of tool (eg, López, García, De la Fuente & De la Fuente, 2007; Ruiz-Ruano, 2015). If the data point in the same direction as the hypotheses, our work could be useful from the clinical or applied point of view when planning interventions to prevent or approach problems related to excessive mobile phone use.

Method

Participants

The non-probabilistic sample selected by means of a snowball-type method consisted of 1176 participants in total, with 348 men (29.6%) and 828 women (71.4%). Ages ranged from 16 to 82 (M = 30.97, SD = 12.05). Participants who lived with a partner (38.4%) or were married (21.3%) made up 59.7%, followed by those were single (36.3%), divorced (2.5%), widowed (0.3%), and 1.1% who indicated that they had a different marital status to those listed above. Regarding the level of education, most of the sample indicated that they had a university degree (64.8%), 0.4% indicated that they had no schooling, and the rest stated that they had completed higher secondary schooling or vocational training, lower secondary or primary schooling. Regarding professional status, 44.5% of participants said they were workers, 37.8% students, 9.9% were unemployed, 2.4% were retired, and 2% indicated that they were housewives.

Instruments

A questionnaire was developed using Google Forms® to gather sociodemographic information (age, sex, marital status, educational level and employment status) as well as information relating to smartphone use (most used application, time of use, reasons for use and number of phones). The questionnaire included a question about the application that was most frequently used on the mobile device, and the responses were recoded to represent the participant's preference for social networks over other applications available on their phones. The questionnaire also included a scale to assess the level of addiction to the smartphone and a questionnaire to assess the level of experiential avoidance.

The smartphone addiction scale used (SAS-SV) is the short version of the smartphone addiction scale (SAS) originally created by Kwon et al. (2013a). The internal consistency of this reduced version designed by Kwon, Kim, Cho & Yang (2013b) is $\alpha = .91$. In this study we have used the adaptation to Spanish by López-Fernández (2015), which obtained a Cronbach's α of .88 in the corresponding adaptation study. The scale consists of ten items based on substance dependence and the pathological gambling disorder described in DSM-IV (APA, 1994, 2000). The response format is presented on a 6-point Likert scale, where 1 corresponds to "strongly disagree" and 6 to "strongly agree". Scores range from 10 to 60, with higher scores representing greater risk of smartphone addiction. The internal consistency indices obtained in this study for the SAS-SV scale are: $\alpha = .87$, 95% CI: .86, .89, and $\omega = .88$.

To measure experiential avoidance, or cognitive inflexibility, we used the version of the Acceptance and Action Questionnaire (Acceptance and Action Questionnaire II or AAQ-II) presented by Ruiz, Langer, Luciano, Cangas & Beltrán (2013). The first version of this test was developed by Hayes et al. (2000) and Hayes et al. (2004); this was based on different clinical experiences and obtained an internal consistency alpha of .7. Bond et al. (2011) developed the second version of the test, which achieved higher internal consistency levels (.97) and contained fewer items. The test consists of seven items with Likert-type responses on a 7-point scale to reflect the degree of truthfulness that the participant attributes to each item according to their experience. In our application of the test, the observed values of internal consistency were: $\alpha = .89$, 95% CI: .89, .90, y $\omega = .90$.

Procedure

The electronic questionnaire was made available to participants via the WhatsApp® instant messaging application, social networks (Facebook® and Twitter®) and email. To begin data collection, we asked university students to complete the form and then distribute it among their contacts on social networks. The questionnaire began with an outline of the study's objectives, a data anonymity and confidentiality guarantee, and a request to share the form among their social network contacts. The dissemination of the form and collection of data began on November 24, 2016 and ended on January 30, 2017.

Data analysis

The analytical strategy used is in line with the proposal of Cohen, Cohen, West & Aiken (2003), which takes correlational models as a general framework for studying behaviour. For example, the correlations between quantitative and dichotomous variables (such as having more than one mobile phone or not) were estimated as standardized coefficients in the corresponding linear regression models which would explain the quantitative variable depending on group membership in the dichotomous variable. To obtain the matrix of correlations between the study variables and the Bayes factors favouring the alternative to the null hypothesis (BF_{10}), we used version 0.9 of the JASP statistical software (JASP Team, 2018).

The resulting Bayes factor expresses how much more true or probable the alternative hypothesis is against the null hypothesis (Kass & Raftery, 1995). A Bayes factor equal to one would indicate that the alternative hypothesis is just as likely as the null hypothesis, given the observed data. A Bayes factor greater than one would indicate how much more likely the alternative hypothesis is against the null hypothesis. For example, a BF_{10} equal to two indicates that the alternative hypothesis is twice as likely as the null hypothesis, while a BF_{10} of 100 means that the alternative hypothesis is 100 times more likely than the null hypothesis. The default Cauchy distribution ($r = 1$) suggested by Rouder, Speckman, Sun, and Morey (2009) was used to estimate the Bayes factors. Simulation studies carried out so far (Jeon & De Boeck, 2017) have shown that such a distribution offers a balanced option regarding the key elements involved in statistical decision making.

The structural models of Bayesian networks were estimated with version 4.2 of the "bnlearn" package (Scutari, 2010) for R. Six different algorithms were used to find the model that best fitted the data. Two of the algorithms used restricted model methods (*Grow-Shrink and Incremental Association*), two were based on fit (*Hill-Climbing and Tabu Search*), while the remaining two were mixed (*Max-Min Hill-Climbing and Restricted Maximization*). We used two different methods to study the goodness of fit of the models estimated by each algorithm. First, the sample was divided into an estimation set containing 70% of the observations, with the remaining 30% (test subset) being used to assess the degree to which the data fit the models established in the estimation phase. Goodness of fit was validated by means of log likelihood, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC) (Scutari & Denis, 2014). In each case, the higher the values, the better the model-to-data fit. The second validation procedure consisted of randomly dividing the data set into equal parts 2000 times to measure the log-likelihood differences from one estimate to another (Koller & Friedman, 2010). In this case, lower log-likelihood loss values would mean a better fit. Finally, to calculate the strength of association of each link in the Bayesian network, the changes in log likelihood, the AIC and the BIC were analysed by deleting the corresponding edge from the model (Scutari & Denis, 2014). In this case, the smaller the log likelihood, AIC or BIC values when a link is removed from the model, the more relevant or influential that link is considered to be for the network tested. Thus, the goodness-of-fit statistics assess the degree to which the model weakens when a link is eliminated from it. The smaller the value of this statistic, the more the model is thought to weaken if the link in question is deleted.

Results

As can be seen in Table 1, the variables which are most closely and positively associated are the number of hours in which the smartphone is used and the time spent on the preferred application. The second largest positive correlation is that between the experiential avoidance score measured with the AAQ-II and the smartphone addiction score on the SAS-SV scale. Experiential avoidance also correlates positively and significantly with the time users spend on their preferred application and the hours of mobile phone use. There is also a positive relationship of the same strength between the SAS-SV addiction score and the hours of mobile phone use, as well as with the time spent on the preferred application. As can be seen in Table 1, the estimated Bayes factors for these correlations suggest that the observed data could be considered as decisive evidence ($BF_{10} > 100$) in favour of the correlations between these variables being genuinely different from zero (Jeffreys, 1948). In other words, given the Bayes factors associated with these correlations, we could say that the hypothesis of genuine correlation between these variables is at least 600 million times more probable (Bayes factor associated with the correlation observed between experiential avoidance and hours of smartphone use) than the null hypothesis.

The results show (Table 1) that the hours spent on the smartphone, the time dedicated to the preferred application and the preferred use of social networks are linked to the female sex. Although the estimated correlations are of a small magnitude, the Bayes factors obtained suggest that the observed data provide very strong evidence in favour of the relationship between these variables. In all three cases, the Bayes factors estimated in favour of the alternative hypothesis are greater than 100, and following the proposal of Jeffreys (1948), this suggests that the observed data provide decisive evidence in favour of the idea of genuine correlation between the variables. On the other hand, there are no significant correlations between the number of years of smartphone use, the preferred use of social networks, and experiential avoidance. There is also no noticeable correlation between years of use and the use of social networks.

Table 2 shows the goodness-of-fit results for the estimated graphical models with each of the algorithms used,

Table 1. *Correlation coefficients adapted to variable type (Cohen et al., 2003), classical p-value of statistical contrast, classical 95% confidence interval (lower left triangle) and Bayes factor favouring the alternative hypothesis or BF10 (upper right triangle).*

	SEX	NA	HM	YM	MOM	TPA	EA	SAS	SN
SEX	—	35377	2780	0.259	4414	1246	0.165	0.067	2.34×10^{7}
NA	.11 < .001 [.05, .17]	—	0.327	4.24×10^{7}	0.905	0.065	0.071	12510	0.041
HM	-.09 0.003 [-.14, -.03]	.06 0.036 [.004, .12]	—	0.039	0.294	9×10^{99}	6.11×10^{8}	5.97×10^{26}	122162
YM	-.06 .048 [-.12, -.001]	.16 < .001 [.10, .21]	.009 0.747 [-.05, .07]	—	10132	0.038	0.037	0.210	0.037
MOM	.09 .002 [.03, .15]	.07 .011 [.02, .13]	.06 0.041 [.002, .12]	.10 < .001 [.04, .16]	—	0.110	0.039	0.066	3436
TPA	-.08 .008 [-.14, -.02]	.03 .284 [-.03, .09]	.82 < .001 [.80, .84]	-.007 .808 [-.07, .05]	.04 .138 [-.01, .10]	—	5.84×10^{12}	2.86×10^{27}	3077
EA	-.05 0.083 [-.11, .01]	-.03 .253 [-.09, .02]	.20 < .001 [.14, .25]	.000 .987 [-.06, .06]	.01 .733 [-.05, .07]	.24 < .001 [.18, .29]	—	1.22×10^{31}	0.042
SAS	-.03 0.276 [-.09, .03]	.10 < .001 [.04, .16]	.33 < .001 [.27, .38]	.06 .062 [-.003, .11]	.03 .279 [-.03, .09]	.33 < .001 [.28, .38]	.35 < .001 [.30, .40]	—	403.9
SN	-.15 < .001 [-.21, -.09]	-.01 .641 [-.07, .04]	.12 < .001 [.06, .17]	.004 .891 [-.05, .06]	-.09 .003 [-.15, -.03]	.14 < .001 [.08, .20]	-.02 .604 [-.07, .04]	.13 < .001 [.07, .18]	—

Note. SEX: sex (1 = male, 0 = female), NA: number of applications installed on smartphone, HM: hours per day spent using mobile phone, YM: years of experience using mobile phones, MOM: owning more than one mobile phone (0 = no, 1= yes), TPA: time spent daily on preferred application, EA: score on experiential avoidance scale AAQ-II, SAS: score on smartphone addiction scale SAS-SV, and SN: considering social networks to be preferred application type (0 = no, 1 = yes). All contrasts are bilateral.

applying the 70/30 partition of the data as described above. The *tabu* and *hc* algorithms generate identical graphs, in the same way that the *rsmax2* and *mmhc* algorithms agree in their estimates. However, as shown in Table 2, the *tabu* and *hc* algorithms obtain the best goodness-of-fit indices when the models are estimated with 70% of the data. The *IAMB* algorithm is the one yielding the worst goodness-of-fit indices. When the remaining 30% of data are used to assess model overfitting, it can be seen that the *gs* algorithm is slightly better. The *mmhc* and *rsmax2* algorithms take second place while *hc-tabu* come third. Again, the *IAMB* turns out to be the worst of the algorithms. However, as shown in Figure 1, when cross-validation is performed using 2000 random partitions of the data, the best algorithms for estimating the structure of dependency contained in the data are *hc* and *tabu*.

The estimated graphical model with the *hc* and *tabu* algorithms, which can thus be considered the most acceptable, is shown in Figure 2. As can be seen, the variables sex and years of mobile phone use are the only ones that do not depend on any other variable. The smartphone addiction score on the SAS-SV scale depends on experiential avoidance, social networks being the preferred application type, and the number of applications installed on the mobile device. The graph also shows that the number of hours spent on the mobile phone depends on the levels of experiential avoidance, the preference for the use of social networks and the score on the mobile phone addiction scale.

Table 2. *Goodness-of-fit indices for each algorithm using 70% of the data for the estimation and the remaining 30% to assess overfitting.*

Algorithm	TABU	HC	RSMAX2	MMHC	GS	IAMB
ABF	1.44	1.44	1.1	1.1	1.22	0.78
Number of tests	288	140	245	220	212	292
Nodes	9	9	9	9	9	9
Arcs	13	13	10	10	11	7
Parameters	22	22	19	19	20	16
LL-70	-15843.82	-15843.82	-15855.34	-15855.34	-15862.58	-16340.11
AIC-70	-15865.82	-15865.82	-15874.34	-15874.34	-15882.58	-16356.11
BIC-70	-15917.5	-15917.5	-15918.98	-15918.98	-15929.56	-16393.7
LL-30	-6911.77	-6911.77	-6914.6	-6914.6	-6917.08	-7085.75
AIC-30	-6933.77	-6933.77	-6933.6	-6933.6	-6937.08	-7101.75
BIC-30	-6985.46	-6985.46	-6978.23	-6978.23	-6975.6	-7132.57

Note. ABF: average branching factor, TABU: *tabu search* algorithm, HC: *hill-climbing* algorithm, RSMAX2: *restricted maximization* algorithm, MMHC: *max-min hill-climbing* algorithm, GS: *grow-shrink* algorithm, IAMB: *incremental association* algorithm, LL: log-likelihood algorithm, AIC: Akaike Information Criterion, and BIC: Bayesian Information Criterion.

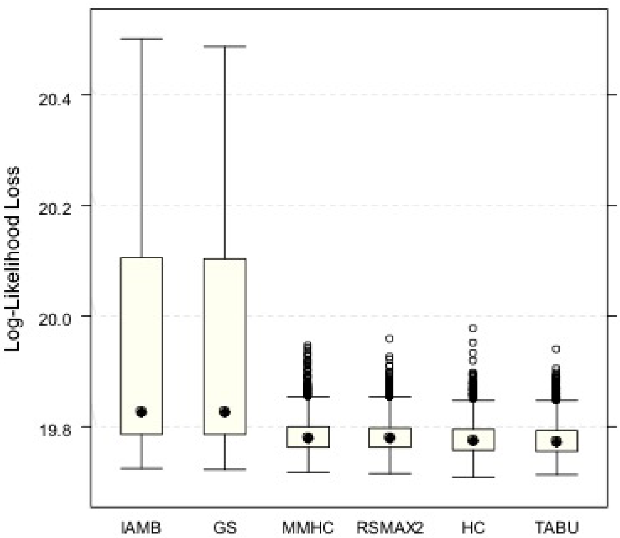

Figure 1. Results of cross-validation analyses.

Note. Log-likelihood loss for each of the 2000 partitions made in the database. The box plots are arranged in descending order by median.

In order to assess the relevance of the graph's edges, the impact of deleting each one was estimated. Table 3 shows the weakening that occurs in the main goodness-of-fit indices of the new model when a particular link is eliminated from the estimated graph (Figure 2). The greater the reduction in the BIC and related statistics on removing a link, the more relevant that link can be considered in the model obtained. Thus, the most relevant link of the model presented in Figure 2, and the one that weakens all goodness-of-fit indices when eliminated from the model, is between the hours per day of mobile phone use and the hours per day spent on the preferred application (see Table 3). The second strongest link identified in the model is between experiential avoidance and the score on the smartphone addiction scale. These two links, together with that linking the SAS-SV score and the number of hours spent on the mobile phone would be the most relevant arcs of the

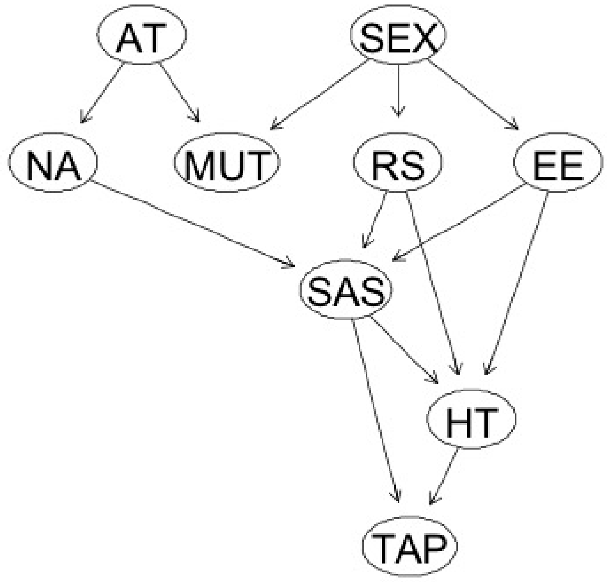

Figure 2. Estimated Bayesian network model with *tabu* and *hc* algorithms.

Note. AT: YM: years of experience using mobile phones, SEX: sex, NA: number of applications installed on smartphone, MUT: MOM: owning more than one mobile phone, RS: SN: considering social networks to be preferred application type, EE: EA: score on experiential avoidance scale AAQ-II, SAS: score on smartphone addiction scale SAS-SV, HT: HM: hours per day spent using mobile phone, and TAP: TPA: time spent daily on preferred application.

Table 3. *Change in goodness-of-fit on removing a directed link from the Bayesian network.*

From	To	LL	AIC	BIC
HM	TPA	-587.06	-586.06	-583.71
EA	SAS	-80	-79	-76.66
SAS	HM	-42.72	-41.72	-39.37
SEX	SN	-13.41	-12.41	-10.06
YM	NA	-14.01	-13.01	-10.66
SN	SAS	-12.02	-11.02	-8.67
NA	SAS	-8.79	-7.79	-5.44
SAS	TPA	-7.77	-6.77	-4.42
SEX	MOT	-5.5	-4.5	-2.15
EA	HM	-6.17	-5.17	-2.82
SN	HM	-4.58	-3.58	-1.23
YM	MOT	-6.33	-5.33	-2.99
SEX	EA	-1.51	-0.51	1.84

Note. SEX: sex, NA: number of applications installed on smartphone, HM: hours per day spent using mobile phone, YM: years of experience using mobile phones, MOM: owning more than one mobile phone, TPA: time spent daily on preferred application, EA: score on experiential avoidance scale AAQ-II, SAS: score on smartphone addiction scale SAS-SV, SN: considering social networks to be preferred application type, LL: log-likelihood, AIC: Akaike Information Criterion, and BIC: Bayesian Information Criterion.

model. If these links were eliminated from the model, the goodness-of-fit indices would weaken. In other words, these are the most strongly established relationships among the variables included in the model. Conversely, the link between sex and experiential avoidance is the least strong and could be eliminated from the model without drastic repercussions on the estimated goodness-of-fit indices.

Discussion

The aim of this study was to investigate the relationship between a range of variables which can be linked to smartphone addiction or problematic use of the same and of social networks. The first idea to be tested was whether a relationship between the experiential avoidance variable and the excessive use of mobile phones existed. Results show that this is indeed the case, both when analysing the correlations obtained between them, and in the Bayesian network which was generated. This result raises the possibility that the smartphone is used as an escape route for negative emotions and thoughts. These outcomes are consistent with some of the recent work published by Chóliz et al. (2009) and Carbonell et al. (2012), who point out that women use it to cope with unpleasant moods or to alleviate emotional distress, which is also noted by García-Oliva & Piqueras (2016). If the pattern of mobile phone use is conditioned by the avoidance of internal negative sensations, it could lead to long-term problems. The directional relationship observed between experiential avoidance and mobile addiction suggests that the latter depends on the former, as also seems to be the case in other addictive disorders (eg, Buckner & Zvolensky, 2014; Garey et al., 2016; Hayes et al., 1996; Levin et al., 2016; Watson et al., 2017). However, as this is an exploratory correlational study, these dependency relationships must be interpreted with caution and investigated with other research methodologies which allow us to more accurately approach causal explanations. In any case, our data suggest that a non-adaptive use of the mobile is related to experiential avoidance, and it would therefore be desirable to pay attention to this fact both from a clinical and scientific point of view.

Although we expected to find a link between levels of experiential avoidance and the use of social networks, the existence of a direct relationship between these variables was not observed. It should be taken into account, however, that mobile addiction is a convergence variable (a potentially common effect) with respect to social network use and experiential avoidance. Therefore, given the formalism of the Bayesian networks, experiential avoidance and social networks become conditionally dependent when the level of mobile addiction is known. In any case, the estimated Bayesian network model suggests that the relationship observed between these variables is mediated by sex. In this sense, as predicted and as stated, for example, by Chóliz et al. (2009), Gil et al. (2015) and Tresáncoras et al. (2017), there is a relationship between sex and excessive smartphone use. However, according to results obtained, this relationship may also be conditioned by the use of social networks (Figure 2). In this as in previous studies, it has been observed that women use smartphones more than men in terms of time spent on social networks, which usually also happens to be their most preferred application type. Looking at it graphically, we see that the relationship between sex and hours of mobile phone use is mediated by considering social networks to be the preferred application type (Figure 2).

From a theoretical point of view, our results are consistent with the hypernatural monitoring model of smartphone addiction (Veissière & Stendel, 2018). This theory holds that there is not something intrinsically addictive in the mobile phone. Rather, Veissière and Stendel (2018) suggest that mobile addiction is a consequence of social expectation in terms of the rewards obtained by connecting with other people. This social component could explain both the onset and maintenance of smartphone addiction, as well as the neurophysiological dimension observed in addictions to substances and other behavioural addictions (eg, Bohbot, Del Balso, Conrad, Konishi & Leyton, 2013; Sussman, Harper, Stahl & Weigle, 2018). Our results provide support for this theory since the levels of smartphone addiction can be explained, partially at least, by the interaction with social networks and as a consequence of the systematic avoidance of unpleasant internal experiences. In any case, although this theory needs to be tested empirically, especially regarding neurophysiological correlates, our results are consistent with its postulates.

Except for gambling addiction, DSM-5 (APA, 2013) does not include behavioural addictions. However, despite the positive consequences that may arise from the use of information technologies, for example, the smartphone, it is noted that there are also negative consequences of their excessive or non-functional use. Thus, Potenza, Higuchi & Brand (2018) advocate continuity in the study of behavioural addictions in order to improve intervention strategies; the focus here should not only be on pathological gambling, but also on other types of behaviour that can lead to addictions. As this study has shown, it seems that experiential avoidance plays some role in relation to excessive mobile phone use. We therefore suggest further research into whether interventions for this type of problem should aim at favouring greater contact with oneself, and, as part of all mindfulness-based interventions, pay greater attention to internal states regardless of whether they are positive or negative. If, as can be deduced from our results, some people use the mobile to escape or avoid negative emotions by looking for a certain type of immediate relief, negative consequences could result for the individual in the long term, presumably leading to behavioural addiction.

One of the limitations of our work is that it is a correlational and exploratory study (Nosek, Ebersole, DeHaven & Mellor, 2018). While these types of study are useful, longitudinal and even experimental studies would be necessary to really analyse the impact of some variables on others. Although our results suggest the existence of a relationship between experiential avoidance and the maladaptive use of the mobile, it could be interesting to carry out studies comparing people with a clinical diagnosis of this disorder to the general population and observing the behavioural patterns in both groups. Another limitation of the study has to do with the data collection procedure. Despite allowing access to a broad spectrum of participants, certain variables cannot be controlled, such as social desirability in questionnaire responses. Moreover, there have not been any studies by age investigating differences between age groups or different life stages. It must be remembered that the age range of the participants studied is very wide, and this dispersion could have affected the results obtained in some way. Future research could have an impact on these aspects given that, as suggested by Odgers (2018), the consequences of technology use are not the same for each person or the developmental stage in which they find themselves.

We urge that one of the future lines of research should investigate whether or not excessive behaviours regarding the use of information technologies can be classified as addictive. As noted by Potenza et al. (2018), the understanding of the biological, psychological and social processes which are at the root of behavioural addiction can improve both prevention and treatment strategies. In any case, we should advocate good use of smartphones or technology in general to make our lives in society more beneficial. It is not a matter of prohibiting or rejecting technologies because they are misused, but rather, as Abelson (1997) suggests in the context of statistical data analysis, of education regarding their proper use.

Conflict of interest

The authors declare no conflicts of interest.

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