Love, desire, and problematic behaviors: Exploring young adults' smartphone use from a uses and gratifications perspective

Abstract

In light of the pervasive adoption of smartphones, scholars have explored the consequences of problematic (i.e., excessive and uncontrolled) use of this technology. Studies have often shown that individuals who spend much time using smartphones experience symptoms similar to those of substance addiction. However, considering the number of hours employed on smartphones as a criterion for measuring problematic use does not account for what people do with their smartphones and why. This study aims to understand what gratifications are related to smartphone usage time and problematic use. Secondly, it aims to understand whether different usage profiles are identifiable from those gratifications and how they differ in terms of problematic use, time-of-use, and socio-demographic characteristics. The data from 528 Italian university students had been collected through a cross-sectional design. Through regression analyses, we found that smartphone gratifications differentially predict the amount of time spent using the smartphone and the level of problematic use that students exhibited. Using the K-means clustering technique, we identified five usage profiles that differed in the amount of time spent using smartphones and, to a greater extent, in their problematic use levels.

Keywords:

Smartphone gratifications; Problematic smartphone use; Smartphone usage profiles; Smartphone usage time; Uses and gratifications

Public Policy Relevance Statements

This work is relevant to the debate about the benefits and risks associated with smartphone use. It shows that using the quantity of smartphone use as a proxy for its problematic use would be an oversimplification and that we must also consider the quality of use. As the results show, problematic smartphone use is more associated with certain types of gratifications (such as avoiding face-to-face contact) than others (such as preparing and discussing schoolwork).

Love, desire, and problematic behaviors: Exploring young adults' smartphone use from a uses and gratifications perspective

Worldwide, a high percentage of people own and use smartphones. An average of 76% of adults in most European countries, the US, Australia, South Korea, and Japan, report that they own a smartphone (O'dea, 2021). In Italy, 71 % of the population own at least one smartphone, indicating a high level of penetration of such technology (Pew Research Center, 2019). We bring our devices everywhere and, in most of our daily activities at work and during leisure time, we rely on them. Even though smartphones help perform numerous personal and social functions, research has shown that excessive and uncontrolled use - Problematic Smartphone Use (PSU; Billieux, 2012) - can be associated with substantial negative consequences for some individuals. In line with Sohn and colleagues (Sohn et al., 2019, p.358), we define PSU as "smartphone use associated with at least some element of dysfunctional use, such as anxiety when the phone was not available, or neglect of other activities" . Research has explored correlates of PSU, and found, for example, that PSU is associated with depression, anxiety (De-Sola Gutiérrez et al., 2016; Elhai, Dvorak, et al., 2017), and low self-esteem (Hong et al., 2012), notably in adolescents and young adults. PSU is also related to increased conflict with others, lowered social skills and emotional intelligence (Scott et al., 2017) and lower psychological well-being (Kumcagiz & Gunduz, 2016). Concern has been raised over the potential negative impact that smartphone use might have on users' behaviors and cognitive abilities. Research has shown that PSU is related to compromised inhibitory control (Chen et al., 2016), impaired attention, and impulsivity (Hadar et al., 2017). Relatedly, heavy smartphone usage correlates negatively with academic progress and success (Samaha & Hawi, 2016). The accumulated evidence presents a rationale for a justified concern surrounding the possible negative psychological consequences of smartphone overuse and its addictive potential. Although parallels exist between classically defined addiction and excessive smartphone use, conceptualizing PSU as a form of addiction may be unjustified (Panova & Carbonell, 2018) as the empirical evidence of behavioral and neurobiological similarities between PSU and substance addiction is inconsistent.

Studies of behavioral addiction have contended that individuals who engage excessively in certain behaviors (i.e., dedicate much time to the activity of interest) experience a common set of symptoms frequently associated with substance addiction, such as salience (i.e., the activity becomes a dominating aspect), tolerance (i.e., more activity is needed to feel activity previous effect), and withdrawal (i.e., the abrupt termination of the activity results in unpleasant feelings, psychologically and/or physiologically) (Kardefelt-Winther et al., 2017). Although using the time spent with the smartphone as an indicator of PSU may seem objective and straightforward, it can be criticized because it overlooks that smartphone use is a normalized part of everyday life in many societies today (Panova & Carbonell, 2018). Also, perhaps more importantly, smartphone usage time does not capture the essence of what people are doing with their smartphones and why (King et al., 2018). While individuals who score high on a PSU scale often use their smartphones for a longer time (De-Sola Gutiérrez et al., 2016), the time individuals spent using smartphones may also indicate other things, such as a promotion at work or a new relationship. Thus, a deeper analysis of uses and gratifications associated with smartphone usage becomes necessary as the gratifications associated with using the smartphone for a lot of time are not necessarily the same that are associated with its problematic use. According to the Uses and Gratification (U&G) theory (Katz & Blumler, 1974), individuals choose to use a specific media if it can satisfy their perceived needs and desires (Baxter et al., 2008). Based on this theoretical framework, Vanden Abeele (2016) identified eight gratifications derived from smartphone usage on a sample of Flemish adolescents: kill time and boredom (i.e., pass-time), express status and identity (i.e., status), feel safer in case of an emergency (i.e., security), make arrangements or let people know of one's availability (i.e., micro-coordination), prepare and discuss school-work (i.e., school), express love for the partner (i.e., love), keep up with family and friends (i.e., relations), and avoid face-to-face contact (i.e., avoidance).

In their comprehensive review, Panova and Carbonell (2018) discussed the extant work on what the literature often referred to as “smartphone addiction”, and evaluated the strength of the evidence that smartphone usage may indeed become a behavioral addiction against the clinical criteria used to diagnose addictive disorders. In light of the evidence available, the authors found that while it is indeed the case that individuals may engage in PSU, the use of the term “addiction” seems unwarranted by the existing data. Interestingly, authors working in the area of PSU (see Elhai et al., 2017; Panova & Carbonell, 2018; Sohn et al., 2019) note that smartphones serve different uses and functions and this could be the reason why users spend a long time on them. Therefore, while it is possible to identify some negative characteristics and outcomes of PSU which are comparable to other behavioral addictions, the use of the term addiction in the context of smartphone use would require excluding that the availability of the smartphone facilitates engaging in other addictive behaviors, rather than being addictive per se. These addictive behaviors would be the real issue rather than smartphone use.

Further, excessive reliance on the smartphone, and its associated problems (i.e., PSU) could be due to a combination of one or more non-addictive behaviors. Just like Supermarkets, by providing a range of (healthy and unhealthy) products which were once available in separate - independent - shops, have often become the one-stop-shop for many consumers, it could be that smartphones are becoming a one-stop-shop where users can satisfy several - different - needs and seek different gratifications, not all of which are necessarily problematic.

The present research directly tests this idea: in other words, this study aims to understand whether and what gratifications are related to smartphone usage time and PSU. Understanding why and how smartphones are utilized will help create usage profiles, which could help better understand PSU levels, time-of-use patterns, and socio-demographic characteristics.

We, therefore, aim to provide initial evidence contributing to the theoretical distinction between PSU and addiction, by demonstrating firstly that distinctive uses are differently associated with mobile phone use, and not all of these uses are problematic. Secondly, identifying which usage patterns are more strongly associated with PSU can help better understand the phenomenology of PSU and devise targeted interventions.

Method

Sample and Procedure

This study used a cross-sectional online data gathering technique. Participants were recruited in April 2020 through a link posted on social media and asked to answer a questionnaire. The questionnaire contained 70 items and required approximately 20 minutes. Participants were required to evaluate each item to proceed through the questionnaire. The Commission for Research in Psychology of our University approved the study (Approval no. RM 220-277).

Five hundred and twenty-eight university students participated, 369 were female (70%), and the mean age was 22.38 years (SD = 2.06, range = 18 - 29 years old). The sample was composed of emerging adults who had a student status (Arnett, 2007). Careless responding was identified using the Self-Reported Single-Item "Use-Me" question (Meade & Craig, 2012). Five additional respondents were either above the age of 29 or were not students, and nineteen answered the "Use-Me" question negatively; their data were not considered in the analysis.

Descriptive statistics are provided in Table 1 and correlations in Table S2 of the Supplementary Materials.

Table 1.

Sample descriptive statistics.

Variable		**Values**
Gender	N Female (%)	369 (70%)
	N Male (%)	159 (30%)
Age	Min	18
	Max	29
	Mean	22.38
	SD	2.06
Age first smartphone	Min	5
	Max	18
	Mean	11.64
	SD	1.75
Typical usage time	N Less than 1 hour (%)	81 (16%)
	N Between 1 and 2 hours (%)	164 (31%)
	N Between 2 and 3 hours (%)	160 (30%)
	N Between 3 and 4 hours (%)	79 (15%)
	N Between 4 and 6 hours (%)	32 (6%)
	N Between 6 and 8 hours (%)	12 (2%)
Day before survey usage time	N Less than 1 hour (%)	4 (1%)
	N Between 1 and 2 hours (%)	39 (7%)
	N Between 2 and 3 hours (%)	101 (19%)
	N Between 3 and 4 hours (%)	116 (22%)
	N Between 4 and 6 hours (%)	136 (26%)
	N Between 6 and 8 hours (%)	82 (15%)
	N More than 8 hours (%)	50 (10 %)

Measures

In addition to basic demographic information on age and gender, the survey comprised items for assessing smartphone usage time patterns, PSU, and smartphone usage gratifications.

Mobile Phone Use

With three items, participants were asked at what age they received their first mobile phone, how many hours they used the mobile phone the day before taking the survey (response options: *less than 1 hour*, *between 1 and 2 hours*, *between 2 and 3 hours*, *between 3 and 4 hours*, *between 4 and 6 hours*, and *between 6 and 8 hours*), and how many hours they used the mobile phone in a typical day (response options: *less than 1 hour*, *between 1 and 2 hours*, *between 2 and 3 hours*, *between 3 and 4 hours*, *between 4 and 6 hours*, *between 6 and 8 hours*, and *more than 8 hours*).

Test of Mobile Phone Dependence (TMD; Chóliz, 2012)

The TMD is a 22-item questionnaire that evaluates PSU. The items were designed according to the substance use disorder criteria of DSM-IV-TR. Even though the measure is called Test of Mobile Phone Dependence, we refer to it as an index of PSU, hence avoiding talking about smartphone addiction as this term is controversial, as discussed in the introduction. Ten items (e.g., “When I am bored, I use my mobile phone”) are answered on a Likert-type scale ranging from 1 (*never*) to 5 (*frequently*), the other 12 (e.g., “I need to use my mobile phone more and more often”) on a Likert-type scale ranging from 1 (*completely disagree*) to 5 (*completely agree*). The scale items were validated on an Italian sample of adolescents and showed good psychometric properties (Vezzoli et al., 2021). In this study, a shorter version of the TMD was used, composed of 20 items out of 22. For two items (12 and 17), concerns about face validity emerged from a small pilot study on 12 participants. The used items have reached satisfying reliability in our sample ($\alpha = 0.86$).

Uses and Gratification Scale (U&G; Vanden Abeele, 2016)

The Uses and Gratification scale consists of 31 items grouped in 8 dimensions (i.e., pass-time, status, security, micro-coordination, school, love, relations, and avoidance). Items are answered through a 5-point Likert scale, from 1 (*not at all*) to 5 (*very much*), indicating how much the claims made about smartphone uses are true for respondents. The Italian translation of the U&G items is available on OSF (https://osf.io/f3kgv/).

A Confirmatory Factor Analysis with the R package *lavaan* (Rosseel, 2012) indicated that the Italian translation of the U&G items validly measured their underlying constructs (i.e., how much individuals use their smartphone for a given usage type). Given the ordinal nature of the U&G items, the Diagonal Weighted Least Squares was used for parameter estimation (Mîndrilă, 2010). The Italian version of the U&G scale preserved the original factor structure of the original U&G scale and showed satisfactory goodness of fit, TLI = .98; CFI = .98; RMSEA = .064, 90% CI [0.062, 0.068]; SRMR = .071 (van de Schoot et al., 2012). All items factor loadings exceeded the cutoff value of 0.40 (Stevens, 2009) and were significant (Table S1), indicating that the items did relate to their latent factor. The items of each dimension demonstrated good internal consistency (α ranges between .77 to .89; Table S1) save the Micro Coordination items, whose Cronbach's alpha was slightly lower the acceptance threshold (α = .68).

Statistical analysis

To understand the relationship between smartphone U&G and the outcomes PSU and usage time, two regression analyses were performed: a multiple linear regression analysis for the PSU score (continuous variable) and an ordinal logistic regression for smartphone usage time (ordinal variable). In the ordinal logistic regression, the time spent with the smartphone the day before taking the survey was used as the dependent variable. Indeed, it has been reported that the accuracy of self-reports of frequent behaviors (e.g., smartphone use) tends to increase when shorter rather than longer time frames are used (Schwarz & Oyserman, 2001). Next, the K-means clustering technique was used for detecting homogeneous subgroups of smartphone users according to the answers to U&G. The elbow method was used to determine the optimal number of clusters (Schroeder et al., 2018). The level of significance was set to .05. The analyses were performed with R for MacIntosh version 4.0.0 (R Development Core Team, 2021). Besides the built-in *stats* package, *MASS* was used for the ordinal logistic regression (Venables & Ripley, 2002) and *NbClust* (Charrad et al., 2014) for clustering.

Results

Relationship between Uses and Gratification, Duration Pattern, and PSU

A sensitivity power analysis was performed to determine the minimum effect size detectable for each predictor. With a sample size of 528 individuals, a power of .80, eight predictors, and $\alpha = 0.05$, the present sample size was adequate to detect a minimum effect of $f^2 = 0.015$, which is considered a small effect (Cohen, 1988). The analysis was performed with *G*Power 3.1* (Faul et al., 2009). As of the ordinal logistic regression model, we did not find a suitable tool for performing a sensitivity power analysis for the ordinal criterion reported time of use. However, this variable underlies a continuous construct (time of usage) that is measured on an ordinal scale. Taylor, West, and Aiken (2006) showed that in such circumstances the use of ordinal regression causes only a small loss of power, especially when there are five or more categories and they are evenly distributed, as in the present work. Therefore, we might expect that the minimum effect size identifiable with linear regression would be comparable to the effect size identifiable with ordinal logistic regression.

Table 2 presents the regression analysis results, where smartphone usage time and TMD scores are regressed on the U&G scale sub-dimensions. The multiple linear regression reveals that using the smartphone as mean for gaining status ($\beta = 0.334$, $p < .001$), passing time ($\beta = 0.346$, $p < .001$), security ($\beta = 0.093$, $p = .041$), and avoiding face-to-face contacts ($\beta = 0.092$, $p = .014$) are all positively associated with PSU score. The ordinal logistic regression shows that using the smartphone for maintaining relations ($OR = 1.321$, $p = .049$), gaining status ($OR = 1.621$, $p < .001$), passing time ($OR = 1.818$, $p = .001$) was related with higher self-reported smartphone usage time; using smartphone for school ($OR = 0.755$, $p = .004$) was related with lower self-reported smartphone usage time. Therefore, some gratifications predict both PSU scores and self-reported usage time (i.e., status and pass the time), while others exclusively predict PSU scores (i.e., security and avoidance), and others still predict only self-reported usage time (i.e., relations and school). To check for the robustness of the estimated coefficients, we performed the same regression analyses using bootstrap resampling. Table S3 shows that the results are similar and, thus, robust.

Table 2.

Results of regression analyses for predicting PSU scores and self-reported usage time from uses and gratification.

	Problematic Smartphone Use Scores				**Self-Reported Usage Time**			
		95% CI				**95% CI**		
	Beta (SE)	**Lower Limit**	**Upper Limit**	***p***	**OR (SE)**	**Lower Limit**	**Upper Limit**	***p***
Relations	0.085 (0.044)	-0.001	0.171	.053	1.321 (0.141)	1.002	1.742	.048
School	0.043 (0.039)	- 0.033	0.118	.270	0.755 (0.098)	0.623	0.914	.004
Status	0.334 (0.036)	0.263	0.405	< .001	1.621 (0.147)	1.215	2.163	.001
Passtime	0.346 (0.037)	0.274	0.419	< .001	1.818 (0.099)	1.498	2.207	< .001
Security	0.093 (0.045)	0.004	0.181	.041	1.195 (0.119)	0.945	1.511	.137
Avoidance	0.092 (0.037)	0.019	0.165	.014	0.934 (0.096)	0.774	1.127	.476
Love	0.056 (0.036)	- 0.016	0.127	.127	1.128 (0.071)	0.982	1.296	.090
Micro Coordination	0.004 (0.048)	- 0.090	0.098	.933	0.804 (0.163)	0.584	1.107	.181
Adjusted R^2/ Nagelkerke R^2	.386*				.144*			

Note. * $p < .05$.

Users' Profiles of Smartphone Usage

K-means clustering of participants' responses on the U&G measure revealed five clusters across the 528 participants. Figure 1 shows how these clusters differ on the smartphone uses and gratification dimensions.

Figure 1

Clusters description according to the Uses and Gratifications dimensions.

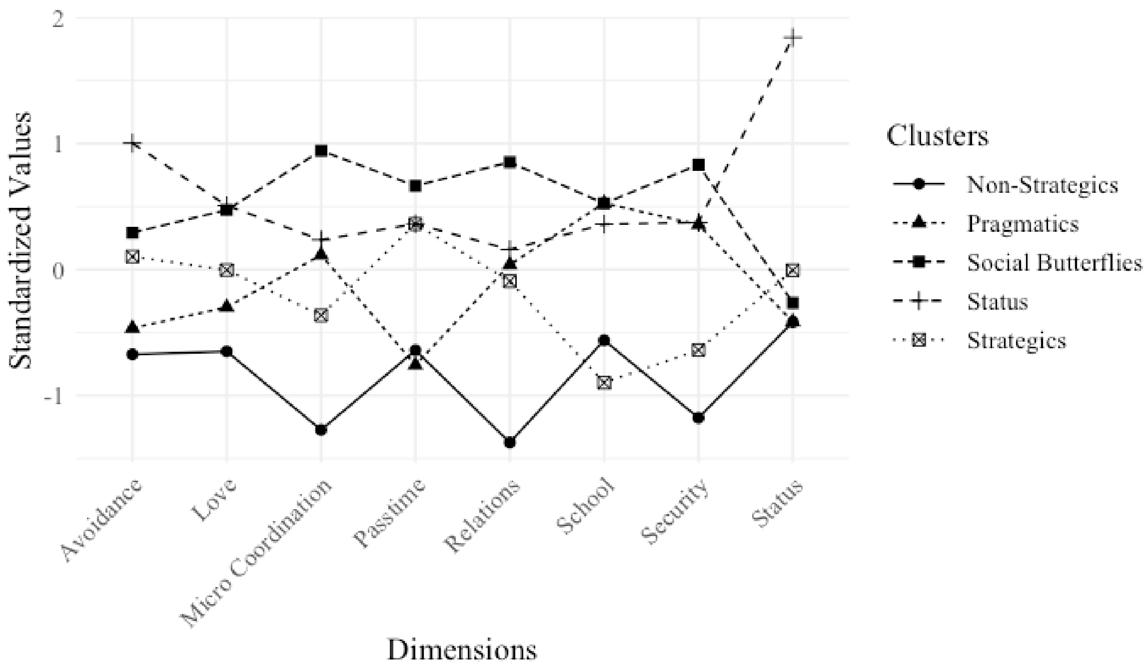

Table S4 reports U&G dimensions means and the standard deviations for each cluster. In addition, we reported the results of the one-way ANOVAs, which tested mean differences between clusters on each U&G dimension. The clusters differ significantly on all dimensions (all p values < .001) with effect sizes that range from large ($\eta^2 = .17$ for love) to very large ($\eta^2 = .51$ for status and security). The "Status" cluster comprises individuals who report using their smartphones predominantly to seek status and avoid face-to-face interactions. The "Pragmatics" cluster includes those who report using it mainly to discuss school projects, make arrangements with others, and be reachable if dangerous events happen. The "Social Butterflies" cluster comprises individuals who score high on the relational facets of smartphone gratifications (e.g., relation, security, school, micro coordination). The "Strategic" cluster comprises individuals who report using their smartphones mostly to pass their time and avoid face-to-face interactions. The "Non-Strategic" cluster comprises those who score low on each dimension of the UGS.

Table 3.

Clusters description by demographic characteristics, self-reported usage time, and PSU score.

		Status	Pragmatics	Social Butterflies	Strategics	Non Strategics	
		N = 66	N = 133	N = 123	N = 127	N = 79	*Total*
Gender	Female (%)	52 (14.1%)	100 (27.1%)	100 (27.1%)	76 (20.6%)	41 (11.1%)	369 (100%)
	Male (%)	14 (8.8%)	33 (20.8%)	23 (14.5%)	51 (32.1%)	38 (23.9%)	159 (100%)
Mean age (SD)		22.67 (2.14)	22.00 (1.82)	23.00 (1.97)	22.31 (2.08)	22.00 (2.44)	
Mean age first mobile (SD)		11.68 (1.72)	11.57 (1.62)	11.51 (1.98)	11.61 (1.61)	11.99 (1.84)	
Median Time Usage		4 (between 3 and 4 hours)	3 (between 2 and 3 hours)	4 (between 3 and 4 hours)	4 (between 3 and 4 hours)	3 (between 2 and 3 hours)	
Mean PSU (SD)		3.28 (0.48)	2.58 (0.54)	3.03 (0.51)	2.79 (0.49)	2.40 (0.49)	

Note. Percentages of female and male respondents were computed by row, so that each percentage represents the likelihood of belonging to that cluster given that an individual is male or female.

Table 3 reports the clusters characteristics pertaining age, gender, age of first smartphone possession, usage time and PSU. We found significant differences between clusters on gender, $\chi^2(4) = 30.11$, $p < .001$; $\Phi = 0.239$, usage time, $H(4) = 25.98$, $p < .001$; $\eta^2 = 0.042$, and PSU, $F(4, 523) = 39.59$, $p < .001$; $\eta^2 = 0.232$. We observed no differences between clusters for participants' age, $F(4, 523) = 0.64$, $p = .64$; $\eta^2 = 0.005$, and age of first smartphone, $F(4, 523) = 1.36$, $p = .25$; $\eta^2 = 0.008$, possibly because the narrow range of values in both the variables.

Discussion

This study aimed to understand whether and how the gratifications related to smartphone usage (Vanden Abeele, 2016) are associated with individuals' smartphone time-of-use and PSU scores. The results of two regression analyses indicated that using the smartphone for signaling status and passing time predicted both PSU scores and self-reported usage time. However, some gratifications exclusively predicted PSU scores but not usage time (i.e., security and avoidance), while others were associated with usage time but not PSU scores (i.e., relations and school). These results suggest that PSU scores and time of use are differentially related to individuals' smartphone gratifications, thus supporting the notion that the time individuals spend using smartphones may not always be a good indicator of PSU (Panova & Carbonell, 2018). Relatedly, the results further emphasize that, in order to understand the emergence of PSU, it is important to consider what people are doing with their smartphones and why they use it. This study considered a set of ways and reasons why people use smartphones, represented by the eight dimensions derived from the U&G theory. Previous research has shown that process usage (e.g., news consumption, entertainment, relaxation) is more associated with PSU than social usage (e.g., social networking, messaging) (Elhai, Levine, et al., 2017; Van Deursen et al., 2015). Other researchers found that PSU levels differ between hedonic, social, and utilitarian gratifications (Gan & Li, 2018). Future research may expand this research area by focusing on other relevant motivations and gratifications for using the smartphone, such as stress relief, spontaneity (Lee et al., 2014), instrumental use, and self-expression (Meng et al., 2020).

Previous research showed, for example, how transdiagnostic psychopathologies can predict the development of PSU (e.g. Rozgonjuk et al., 2019). Our results suggest that other psychological issues (e.g., social anxiety and feeling in danger) could be contributing factors to the development of PSU. Future research should explore the effect of these other psychological issues, and whether addressing the underlying conditions might provide a useful pathway to intervention. It is important to notice, however, that evidence shows that smartphones are at times perceived by the users as "social companions" in and for themselves (Carolus et al., 2019). Future research could explore the relationship between perception of the smartphone as a social companion and PSU.

As gratifications play an important role in defining the relationship between individuals and their smartphones, the second aim of the study was to identify profiles of smartphone usage and understand how these profiles differ. These profiles might help identify specific usage patterns associated with problematic use. This will allow the development of ad-hoc mitigation strategies.

We identified five clusters that differed significantly according to gender, time-of-use, and PSU scores: The Status cluster showed the greatest mean levels of PSU, indicating that those who use their smartphones mostly for signaling status or avoiding face-to-face interactions had a greater probability of showing PSU. Instead, the Non-Strategic cluster showed the lowest mean level of PSU. Smartphone usage time significantly differed across clusters but to a lesser extent than PSU scores. Specifically, individuals in the Pragmatics and Non-Strategic clusters used their smartphones for less time than the other clusters. These results, taken together, tell us that the gratifications individuals gain by using their smartphones are associated differently to the time they pass with such technology and their level of problematic use. Thus, while the identified groups show little difference in the amount of time spent using the smartphone, the motivations for using it are more likely to differentiate the clusters on the level of problematic use.

Finally, women respondents were more numerous in Pragmatics and Social Butterflies clusters. The majority of men fell within the Strategic cluster, followed by Non-Strategics and Pragmatics clusters. This suggests that smartphone use can be linked to socialization patterns (Vanden Abeele et al., 2014; Wilska, 2003). The participants' age and age of first smartphone possession did not differ across clusters.

Overall, gender and time of usage differences between usage profiles suggest that people with different characteristics may have different needs to fulfill and, thus, use the smartphone more or less frequently. For example, heavy users use the smartphone more for gaining status and avoid in-person interactions than soft users do. However, it is worth mentioning that such differences between usage profiles may also signal specific pathways that may lead to the development of PSU. Following the "Supermarket" analogy introduced earlier in this paper, it is not enough to know that the young adult visits the corner store late at night; it is important to see if they buy liquor or groceries. This will help us better understand whether we are in front of a problem. For example, if we found that soft users use the smartphone more in a pragmatic way, i.e., because they need to micro-coordinate and for security reasons, this would kind of reassure us that their increased use of the smartphone is not problematic. However, if they use it more for status, this might be a pointer that we are in front of a problem that needs to be solved.

It should be noted that the data for this research were collected during the Covid-19 epidemic imposed lockdown. The U&G scale asks participants to describe their smartphone usage in general. We cannot assume that participants accurately evaluated their smartphone usage parceling out the use associated with the current lockdown situation. Some of the differences between clusters may have been exacerbated or reduced by the contingent situation of imposed social distancing. In the future, it will be interesting to investigate if the specific pattern of results will remain stable also in the absence of social distancing.

A further limitation of this study was using a self-report measure for assessing individuals' smartphone usage time. Vanden Abeele and colleagues (2013) found that individuals, particularly heavy users, tend to underestimate the time they spend with their smartphones. According to Schwarz and Oyserman (2001), when people have to report frequently occurring behaviors (e.g., smartphone use), the likelihood of getting a biased self-report is higher, possibly because of poor representation of these types of behavior in memory. Thus, estimates of the frequency with which these behaviors occur are hard to make (Tourangeau et al., 2000). Future research could address this aspect by measuring the actual usage time using behavioral data retrieved from participants' smartphones.

However, we believe that, despite the specific lockdown conditions in which the data were collected and the use of the self-reported smartphone usage time, this research delivers two important messages. On the one hand, the results show that individuals' gratifications from using their smartphones differently predict the time spent using them and PSU scores. This suggests that at least theoretically it would be incorrect to consider smartphone problematic use as an addiction. On the other hand, our data show that usage profiles based on individuals' gratifications for using smartphones differ more on the level of problematic use than the amount of time spent using the smartphone. Therefore, our study suggests it would be useful to design interventions aimed at reducing specific uses that are shown to be associated with problematic consequences.

References

Arnett, J. J. (2007). Emerging Adulthood: What Is It, and What Is It Good For? *Child Development Perspectives*, *1*(2), 68–73. https://doi.org/10.1111/j.1750-8606.2007.00016.x

Baxter, L., Egbert, N., & Ho, E. (2008). Everyday health communication experiences of college students. *Journal of American College Health*, *56*(4), 427–436. https://doi.org/10.3200/JACH.56.44.427-436

Billieux, J. (2012). Problematic Use of the Mobile Phone: A Literature Review and a Pathways Model. *Current Psychiatry Reviews*, *8*(4), 299–307. https://doi.org/10.2174/157340012803520522

Carolus, A., Binder, J. F., Muench, R., Schmidt, C., Schneider, F., & Buglass, S. L. (2019). Smartphones as digital companions: Characterizing the relationship between users and their phones: *New Media & Society*, *21*(4), 914–938. https://doi.org/10.1177/1461444818817074

Charrad, M., Ghazzali, N., Boiteau, V., & Niknafs, A. (2014). NbClust: An R Package for Determining the Relevant Number of Clusters in a Data Set. *Journal of Statistical Software*, *61*(6), 1–36. http://www.jstatsoft.org/v61/i06/

Chen, J., Liang, Y., Mai, C., Zhong, X., & Qu, C. (2016). General Deficit in Inhibitory Control of Excessive Smartphone Users: Evidence from an Event-Related Potential Study. *Frontiers in Psychology*, *7*, 511. https://doi.org/10.3389/fpsyg.2016.00511

Chóliz, M. (2012). Mobile-phone addiction in adolescence: the test of mobile phone dependence (TMD). *Progess in Health Sciences*, *2*(1), 33–45.

Cohen, J. (1988). Statistical Power Analysis for the Behavioural Science (2nd ed.). Lawrence Erlbaum Associates.

De-Sola Gutiérrez, J., de Fonseca, F. R., & Rubio, G. (2016). Cell-phone addiction: A review. In *Frontiers in Psychiatry* (Vol. 7, Issue OCT, p. 175). Frontiers Media S.A. https://doi.org/10.3389/fpsyt.2016.00175

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. In *Journal of Affective Disorders* (Vol. 207, pp. 251–259). https://doi.org/10.1016/j.jad.2016.08.030

Elhai, J. D., Levine, J. C., Dvorak, R. D., & Hall, B. J. (2017). Non-social features of smartphone use are most related to depression, anxiety and problematic smartphone use. *Computers in Human Behavior*, *69*, 75–82. https://doi.org/10.1016/J.CHB.2016.12.023

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical Power Analyses Using G*Power 3.1: Tests for Correlation and Regression Analyses. *Behavioral Research Methods*, *41*, 1149–1160. https://doi.org/10.3758/BF03193146

Gan, C., & Li, H. (2018). Understanding the effects of gratifications on the continuance intention to use WeChat in China: A perspective on uses and gratifications. *Computers in Human Behavior*, *78*, 306–315. https://doi.org/10.1016/J.CHB.2017.10.003

Hadar, A., Hadas, I., Lazarovits, A., Alyagon, U., Eliraz, D., & Zangen, A. (2017). Answering the missed call: Initial exploration of cognitive and electrophysiological changes associated with smartphone use and abuse. *PLOS ONE*, *12*(7), 1–16. https://doi.org/10.1371/journal.pone.0180094

Hong, F. Y., Chiu, S. I., & Huang, D. H. (2012). A model of the relationship between psychological characteristics, mobile phone addiction and use of mobile phones by Taiwanese university female students. *Computers in Human Behavior*, *28*(6), 2152–2159. https://doi.org/10.1016/j.chb.2012.06.020

Kardefelt-Winther, D., Heeren, A., Schimmenti, A., van Rooij, A., Maurage, P., Carras, M., Edman, J., Blaszczynski, A., Khazaal, Y., & Billieux, J. (2017). How can we conceptualize behavioural addiction without pathologizing common behaviours? *Addiction*, *112*(10), 1709–1715. https://doi.org/10.1111/add.13763

Katz, E., & Blumler, J. G. (1974). *The uses of mass communication: Current perspectives on gratifications research*. SAGE Publications.

King, D. L., Herd, M. C. E., & Delfabbro, P. H. (2018). Motivational components of tolerance in Internet gaming disorder. *Computers in Human Behavior*, *78*, 133–141. https://doi.org/10.1016/j.chb.2017.09.023

Kumcagiz, H., & Gunduz, Y. (2016). Relationship between Psychological Well-Being and Smartphone Addiction of University Students. *International Journal of Higher Education*, *5*(4), 144. https://doi.org/10.5430/ijhe.v5n4p144

Lee, U., Lee, J., Ko, M., Lee, C., Kim, Y., Yang, S., Yatani, K., Gweon, G., Chung, K.-M., & Song, J. (2014). Hooked on Smartphones: An Exploratory Study on Smartphone Overuse among College Students. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,*. https://doi.org/10.1145/2556288.2557366

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*(3), 437–455. https://doi.org/10.1037/a0028085

Meng, H., Cao, H., Hao, R., Zhou, N., Liang, Y., Wu, L., Jiang, L., Ma, R., Li, B., Deng, L., Lin, Z., Lin, X., & Zhang, J. (2020). Smartphone use motivation and problematic smartphone use in a national representative sample of Chinese adolescents: The mediating roles of smartphone use time for various activities. *Journal of Behavioral Addictions*, *9*(1), 163–174. https://doi.org/10.1556/2006.2020.00004

Mîndrilă, D. (2010). Maximum Likelihood (ML) and Diagonally Weighted Least Squares (DWLS) Estimation Procedures: A Comparison of Estimation Bias with Ordinal and Multivariate Non-Normal Data. *International Journal for Digital Society*, *1*(1), 60–66. https://doi.org/10.20533/ijds.2040.2570.2010.0010

O'dea, S. (2021). *Number of smartphone users worldwide from 2016 to 2021*. https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/

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

Pew Research Center. (2019). *Smartphone Ownership Is Growing Rapidly Around the World, but*

Not Always Equally. https://www.pewresearch.org/global/2019/02/05/smartphone-ownership-is-growing-rapidly-around-the-world-but-not-always-equally/

R Development Core Team. (2021). R: A Language and Environment for Statistical Computing. In *R Foundation for Statistical Computing* (4.0.5). https://www.r-project.org/

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. In *Journal of Statistical Software* (Vol. 48). https://doi.org/10.18637/jss.v048.i02

Rozgonjuk, D., Elhai, J. D., Ryan, T., & Scott, G. G. (2019). Fear of missing out is associated with disrupted activities from receiving smartphone notifications and surface learning in college students. *Computers & Education*, *140*, 103590. https://doi.org/10.1016/J.COMPEDU.2019.05.016

Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior*, *57*, 321–325. https://doi.org/https://doi.org/10.1016/j.chb.2015.12.045

Schroeder, N. L., Yang, F., Banerjee, T., Romine, W. L., & Craig, S. D. (2018). The influence of learners' perceptions of virtual humans on learning transfer. *Computers & Education*, *126*, 170–182. https://doi.org/https://doi.org/10.1016/j.compedu.2018.07.005

Schwarz, N., & Oyserman, D. (2001). Asking questions about behavior: Cognition, communication, and questionnaire construction. *American Journal of Evaluation*, *22*(2), 127–160. https://doi.org/10.1016/S1098-2140(01)00133-3

Scott, D. A., Valley, B., & Simecka, B. A. (2017). Mental Health Concerns in the Digital Age. *International Journal of Mental Health and Addiction*, *15*(3), 604–613. https://doi.org/10.1007/s11469-016-9684-0

Sohn, S., Rees, P., Wildridge, B., Kalk, N. J., & Carter, B. (2019). Prevalence of problematic smartphone usage and associated mental health outcomes amongst children and young people: a systematic review, meta-analysis and GRADE of the evidence. *BMC Psychiatry*, *19*(1), 356.

https://doi.org/10.1186/s12888-019-2350-x

Stevens, J. P. (2009). *Applied multivariate statistics for the social sciences.* (5th ed.). Routledge/Taylor & Francis Group.

Taylor, A. B., West, S. G., & Aiken, L. S. (2006). Loss of power in logistic, ordinal logistic, and probit regression when an outcome variable is coarsely categorized. *Educational and Psychological Measurement*, *66*(2), 228–239. https://doi.org/10.1177/0013164405278580

Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). *The psychology of survey response*. Cambridge University Press. https://doi.org/https://doi.org/10.1017/CBO9780511819322

van de Schoot, R., Lugtig, P., & Hox, J. (2012). A checklist for testing measurement invariance. *European Journal of Developmental Psychology*, *9*(4), 486–492. https://doi.org/10.1080/17405629.2012.686740

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

Vanden Abeele, M., Beullens, K., & Roe, K. (2013). Measuring mobile phone use: Gender, age and real usage level in relation to the accuracy and validity of self-reported mobile phone use. *Mobile Media & Communication*, *1*(2), 213–236. https://doi.org/10.1177/2050157913477095

Vanden Abeele, M., Campbell, S. W., Eggermont, S., & Roe, K. (2014). Sexting, Mobile Porn Use, and Peer Group Dynamics: Boys' and Girls' Self-Perceived Popularity, Need for Popularity, and Perceived Peer Pressure. *Media Psychology*, *17*(1), 6–33. https://doi.org/10.1080/15213269.2013.801725

Vanden Abeele, M. M. (2016). Mobile lifestyles: Conceptualizing heterogeneity in mobile youth culture. *New Media & Society*, *18*(6), 908–926. https://doi.org/10.1177/1461444814551349

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S*. Springer. http://www.stats.ox.ac.uk/pub/MASS4/

Vezzoli, M., Colombo, A., Marano, A., Zoccatelli, G., & Zogmaister, C. (2021). Test for Mobile phone dependence: psychometric properties and confirmatory factor analysis. *Current Psychology*. https://doi.org/10.1007/s12144-021-01449-5

Wilska, T. A. (2003). Mobile Phone Use as Part of Young People's Consumption Styles. *Journal of Consumer Policy*, *26*(4), 441–463. https://doi.org/10.1023/A:1026331016172