Predicting problematic smartphone use over time in adolescence: A latent class regression analysis of online and offline activities

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Abstract

Despite today's ubiquitous nature of smartphones among adolescents, little is known about behavioral online and offline longitudinal predictors of problematic smartphone use (PSU). Guided by Uses and Gratifications Theory, we applied latent class analysis on survey data collected in 2017 from a cohort of 1096 adolescents (M_{age} = 12.4, SD_{age} = .56) and regressed PSU measured one year later on class membership, controlling for socio-demographic characteristics, social desirability, and autoregressive effects. We extracted four distinct classes: *social-recreational onliners* (n=228), *weekend onliners* (n=331), *balanced* (n=404), and *noninvolved* (n=153). Characterised by significantly more time spent online for recreational and social networking activities, both during weekdays and weekend days, as well as less time for sleep, the *social-recreational onliners* class showed significantly higher levels of PSU over time. Future studies should assess not only duration but also the frequency of daily online activities to provide further insights on behavioral predictors of PSU.

Keywords: problematic smartphone use; adolescents; online and offline behavior; latent class; longitudinal

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Introduction

Smartphones have become a ubiquitous part of adolescents' everyday lives. A study from the Pew Research Center showed that 95 per cent of 13 to 17-year-olds in the U.S. have access to a smartphone, and 45% of them on an almost constant basis (2018). A similar picture emerges in Europe where, in Switzerland, 99 per cent of 12 to 19-year-olds own a smartphone device on which they spent, on average, almost 3.5 hours during a weekday and 4.5 hours during a weekend day (Süss et al., 2018). The time component (i.e. excessive use) is one characteristic of problematic smartphone use (PSU). Other characteristics include unsuccessful attempts to reduce smartphone use (relapse), withdrawal symptoms, constant thinking about the smartphone and activities on the device (salience), an increasing urge for use (tolerance) as well as conflict with family members or friends and mood modifications due to excessive smartphone use (Kwon et al., 2013). PSU has many aspects in common with problematic Internet use, and it is closely linked to "nomophobia", which includes symptoms such as discomfort and anxiety caused by being out of contact with a mobile phone (Kwon et al., 2013). However, recent research in the field of addictive disorders has repeatedly pointed out that such characteristics do not meet the severity levels of those caused by a real pathological condition, suggesting to talk about problematic use rather than an addiction (e.g., Panova and Carbonell, 2018). PSU is associated with several mental health problems, especially among adolescents. A systematic review (Elhai et al., 2017) revealed that depression severity is consistently and significantly positively associated with PSU, so are anxiety and stress, yet to a lesser extent, emphasising the importance of studying factors that lead to PSU. It has to be noted, though, that recent studies suggest that there is little clear-cut evidence of a detrimental effect of digital technology use on adolescent well-being (Orben and Przybylski, 2019) and life-satisfaction (Orben et al., 2019), especially considering the magnitude of the effect, which has been defined as "too small to warrant policy change" (Orben and Przybylski, 2019a, p. 173). In the context of social media use, for example, effects are likely to be small and related to personal and contextual factors, as well as anchored to different methodologies implied by the researchers (Orben et al., 2019). Nevertheless, these findings should not hinder the study of factors leading to PSU, which remains a public health concern (Sohn et al., 2019).

Concerning socio-demographic and psychological trait-like predictors, for example, younger age, extraversion, neuroticism, impulsivity, and low self-esteem are all significantly related to experiences of problematic mobile phone use (Bianchi and Phillips, 2005; Pancani et al., 2019). Another study found lower levels of self-control to be related to PSU (Jeong et al., 2016). In addition to these factors, individual motivations and resulting online activities have been associated with problematic use of digital devices (Elhai et al., 2017; Jeong et al., 2016; Kim et al., 2016). Evidence on behavioral factors and their underlying motivations, which will be summarised in the next chapter, is of particular importance since they can be the target of interventions aiming to reduce the risk of developing PSU, especially in the younger population. However, given the predominantly cross-sectional nature of research on primarily online behaviors associated with PSU, more longitudinal research is needed to investigate the wider spectrum of behavioral predictors. Thus, this study aims to identify patterns of daily online and offline activities and explore their impact on PSU over time.

Theoretical background

To make predictions on the impact of behavioral factors on PSU, we can draw on Uses and Gratifications Theory (UGT) (Katz et al., 1974), which states that media (devices), like the smartphone, are actively and selectively used to gratify personal needs for socialisation and community utility, information, passing time, entertainment, and relaxation (Ruggiero, 2000; Whiting and Williams, 2013). Compared to other online and offline sources of gratification, the affordances of the smartphone (e.g., portability, ease of use, multi-functionality, personalisation) facilitate the gratification of a variety of personal needs. The immediate and low-cost nature of needs gratification via the smartphone leads to a repeated use of and, eventually, a problematic use of the device itself (Ruggiero, 2000; Sun et al., 2008). A study with university students on gratifications and problematic Internet use identified seven different gratification factors, including, among others, social bonding, information seeking, aesthetic experience, and diversion, that the authors grouped into process-oriented and content-oriented gratifications (Song et al., 2004). Among all seven factors, process-oriented gratifications such as seeking and maintaining social relations (i.e. social media use) and diversion had the highest predictive power in explaining Internet addiction tendencies. Follow-up research on gratifications and PSU has focused on non-social (e.g., online shopping, news consumption) and social (e.g., SNS use, instant messaging) smartphone use, with mixed results: while some studies found more evidence for social use in the development of PSU (Jeong et al., 2016; Salehan & Negahban, 2013), others found more support for non-social use and PSU (Elhai et al., 2017). To explain the effect of social media use on PSU, Jeong and colleagues (2016) argued that social networking on smartphones is facilitated by its portability and connectivity, which may result in frequent and habitual checking behaviors, indicative of PSU. Conversely, Elhai and colleagues (2017) interpreted the positive relationship found between non-social use and PSU by stating that the hedonic use of a smartphone could be a means to compensate for negative emotion. This interpretation is backed up by another study on motivational predictors of PSU, which has shown that the need for entertainment and escapism predict dependency, especially among people with higher stress levels (Wang et al., 2015). It has to be noted, though, that all cited studies rely on cross-sectional data and, thus, impede conclusions on directionality. Furthermore, they primarily focus on online activities as an answer to psychological needs and motivations and do not consider offline activities, which, according to UGT, represent alternative sources of gratifications sought. Offline activities are more likely but not limited to leisure time activities, like doing sports or passing time with friends. Therefore, a more holistic study applying UGT should consider both online and offline activities to evaluate which patterns of activities contribute to higher levels of PSU. Thus, we aim to detect if and how patterns of different online and offline activities impact PSU over time. To do so, we use latent class regression modelling, which groups individuals into classes based on their common characteristics and differences.

To date, only a few studies have applied latent class analysis in the context of PSU, focusing on the identification of patterns of (problematic) media use. Based on a sample of 653 Korean adolescents, Kim and colleagues (2016) applied this methodology on problematic Internet and smartphone use. Grounded in UGT, they identified six distinct classes with the aim to detect different profiles of media substituters and complementers. They found that about 2.4 per cent presented high levels of PC and smartphone use, where PC gaming was associated with complementation of devices and instant messaging with substitution. In another study on 448 university students in Korea, Mok and colleagues (2014) used latent class analysis focusing once again on problematic usage patterns. Looking at associated personality and psychological well-being factors, they identified three distinct classes for males and females separately, where 26 per cent of males and 17 per cent of females fell in the high Internet and smartphone addiction class. The authors concluded that more information on the hours of use, motivations, and different kinds of use (e.g., applications and contents) should be included in further studies. A somewhat different approach was followed by Foerster and Röösli (2017) on a sample of 895 Swiss adolescents. They considered both online and phone usage behaviors as well as problematic mobile phone use to identify five classes, i.e. a gaming, medium use, low use, call preferences, and high social use class, that the authors associated with a holistic measure of adolescent well-being measured at the same time point. They found that the high social use class, predominantly female, showed the highest levels of problematic mobile phone use. Eventually, Elhai and Contractor (2018) relied on a sample of 296 US university undergraduate students to identify two distinct latent classes of smartphone users (heavy vs light use) by considering different smartphone activities. Using UGT as the theoretical basis, they demonstrated how heavy use (primarily driven by social smartphone activities) is associated with higher levels of PSU, measured cross-sectionally. To summarise, these cited studies are good examples of how latent class analysis can be a fruitful approach to observe specific behavioral and psychological patterns related to smartphone (over-) use on a population level to shed light onto predictors and effects of PSU.

Research questions

A major limitation of previous studies, however, lies in the fact that they considered only online activities. In doing so, they ignored the broader everyday life context shaped by individuals' offline activities, too. UGT explicitly states that people seek gratifications from different online and offline sources. Therefore, the present study aimed to answer the following two research questions:

RQ1: Are there distinct latent classes of adolescents based on both their online (e.g. time spent online and type of online activity) and offline (leisure) activities (e.g. time spent doing sports, with friends, homework, sleep)?

RQ2: How do these classes differ in their socio-demographic characteristics (e.g. gender, socioeconomic status, smartphone ownership) and online and offline activities?

Another limitation of past studies is the use of cross-sectional data to associate latent classes with PSU and well-being outcomes. In contrast, we aimed to use longitudinal data to answer our third and last research question:

RQ3: How does class membership predict PSU one year later?

Methods

Data collection

For the present study, we used two-wave data from a longitudinal study with students from all 35 public and two private middle schools in Canton Ticino, Switzerland. The sample is representative of one-third of students registered in the database of the Cantonal education administration and born in 2004/2005. Wave 1 (T1) data were collected in spring 2017 from grade 7 students, and wave 2 (T2) data in spring 2018 from the same cohort at grade 8 (approximately 12 and 13 years of age). Teachers received a paper-and-pencil questionnaire for each student signed with a student identifier provided by the Cantonal education administration, instructions for administration, and a pre-stamped return envelope. Teachers accessed the database of the Cantonal education administration to extract the corresponding student names and distribute the questionnaire for self-administered completion at school. They collected all completed questionnaires and sent them back to the research team. Of 1460 distributed questionnaires at T1, schools returned 1427 (98%), and of 1419 distributed at T2, they returned 1374 (97%). Sample attrition within each wave was mainly due to students being absent during the day of data collection. Between waves, the sample diminished due to students repeating a school year, switching between private and public schools, or leaving the Canton. In these cases, they could not be tracked any more with the help of a unique identifier, which assured anonymity of all matched data and thereby adequately addressed ethical considerations regarding privacy, required by the Cantonal education administration to approve this form of data collection.

Analytical sample

The analytical sample includes 1096 students (M_{ageT1}= 12.4, SD_{ageT1} = .56, 52.4% female), for which missing data on the predictor and outcome variables were less than 10%. We imputed missing data using the Expectation-Maximization algorithm in SPSS. Difference tests between the analytical sample (AS) and the remainder of the initial sample (RIS) (n = 331) on socio-demographic variables and smartphone ownership at T1 revealed significant differences for gender (proportion of females) (AS = 52.4%; RIS = 43.8%; χ^2 (1, N = 1426) = 7.54, p = .006) and smartphone ownership (AS = 84.7%; RIS% = 65.8%; χ^2 (1, N = 1413) = 56.70, p < .001), while no significant difference was evident for socio-economic status (M_{AS} = 2.84, SD_{AS} = 0.75; M_{RIS} = 2.83, SD_{RIS} = 0.82; t(475.5) = 0.28, p = .779), with 73.2% of adolescents in the analytical sample reporting that their family is economically “well” or “very well” off.

Measures

All variables were measured using self-reports (see Table 2 “Overall sample” for descriptive statistics). Measures for online and offline activities were developed specifically for this study, while previously validated scales were used to measure PSU and social desirability.

Online activities. Online activities at T1 were assessed in terms of duration and types of content. Duration of smartphone and Internet use was measured separately asking participants how much time they usually spend with the Internet-enabled smartphone and on the Internet during a typical school day and a typical weekend day. Students reported the duration on a scale with nine-time intervals, which were reduced to four categories for further analysis (1 = “never”, 2 = “up to one hour”, 3 = “from 1 to 2 hours”, 4 = “more than 2 hours”). Additionally, we assessed ten different online activities (e.g., Internet use for school, news, health-related information, online gaming, online TV, listening to music, social networking, and instant messaging) on a four-point scale (1 = “never”, 2 = “sometimes”, 3 = “often”, 4 = “always”). Questions used to measure online activities and their descriptives are available in Appendix A.

Offline activities. At T1, we assessed how often participants got involved in the following five offline activities during a typical weekday (i.e. time spent doing sports, going out with friends, doing homework, reading books for fun, and sleeping). For each activity, students could choose between nine-time intervals, which were reduced to four categories for further analysis (from 1 = “never” to 4 = “more than 2 hours”). Sleep duration was calculated based on students’ responses on when they went to bed yesterday and when they woke up the following morning. The continuous measure was reduced to a four-point scale (1 = “less than 7 hours”, 2 = “from 7 to 8 hours”, 3 = “from 8 to 10 hours”, 4 = “more than 10 hours”) according to the recommendations of the National (American) Sleep Foundation (NSF, 2015). Questions used to measure offline activities and their descriptives are available in Appendix A.

Problematic smartphone use (PSU). We used the short version of the Smartphone Addiction Scale for adolescents (SAS-SV; Kwon et al., 2013) at both T1 and T2. It is based on a battery of ten items assessed on a five-point scale (from 1 = “strongly disagree” to 5 = “strongly agree”) (M_{t1}= 1.77,

SD_{t1}=.75, α_{t1}=.861; M_{t2}=2.02, SD_{t2}=.88, α_{t2}=.889), which cover daily life disturbance (e.g., missing planned work due to smartphone use), withdrawal (e.g., feeling impatient and fretful when I am not holding my smartphone), overuse (e.g., using my smartphone longer than I intended), tolerance (e.g., people around tell me that I use my smartphone too much) and disposition to online-oriented relationships (e.g., constantly checking my smartphone so as not to miss online conversations between other people).

Covariates. Gender (1 = female), perceived socioeconomic status (0 "not at all good" to 4 "very good", 73.2% reported a good or very good status at T1), smartphone ownership (0 = "not having a smartphone", 1 = "having a smartphone", 85% owned a smartphone at T1), and a 13-item measure of social desirability (Camerini and Schulz, 2018) on a five-point scale (1 = "always" to 5 = "never", M_{t1}=3.24, SD_{t1}=.62, α_{t1}=.763) were included as covariates. Social desirability was added as a covariate to account for potential systematic bias in self-report behaviors.

Statistical analysis

To identify subgroups of adolescents based on their online and offline activities, a latent class regression model was performed using the "poLCA" package (Linzer and Lewis, 2011) in R statistical software. Both offline and online activities at T1 were entered as manifest variables. A latent class regression model is equivalent to classical latent class analysis. The only difference is that the probability of belonging to a specific latent class is also predicted by entered covariates. In other words, by entering (socio-demographic) covariates at this stage, we can exclude the possibility to create spurious latent classes, which are determined primarily by the influence of covariates. Since this type of analysis does not propose the optimal number of latent classes, we ran five different models varying between a 2- and a 6-class solution. We evaluated seven parsimony and goodness-of-fit indices: the Log-Likelihood, the Log-likelihood ratio, the Akaike Information Criterion (AIC) and the conditional AIC (cAIC), the Bayesian Information Criterion (BIC), the sample-size adjusted BIC (SABIC), and the entropy. Moreover, we inspected the distribution of the sample in each class (to avoid classes with less than 10% of participants) and how meaningful and distinct the different classes were to identify the optimal number of classes. For the second step, we analysed possible differences in socio-demographic characteristics, i.e. gender and socioeconomic status, as well as online and offline activities among classes through Kruskal-Wallis non-parametric tests. Separate models were estimated for each of the variables of interest, and post-hoc analyses based on the Dunn's test with Bonferroni correction were further conducted on those variables that showed statistically significant differences across classes. These analyses were conducted to guide the description of classes and the interpretation of the main differences among their members. In the last step, we created a categorical variable containing class membership at T1 for each subject. We regressed PSU at T2 on class membership, controlling for gender, socioeconomic status, social-desirability, smartphone ownership, and PSU at T1. Controlling for autoregressive effects of PSU allows determining the additional predictive value of patterns of online and offline activities and how these patterns change levels of PSU in adolescents over time. In doing so, this study goes beyond cross-sectional research and identifies longitudinal predictors of PSU.

Results

Latent classes

Our first research objective was to identify distinct latent classes of adolescents based on both their online (e.g. time spent online and type of online activity) and offline (leisure) activities (e.g. time spent doing sports, with friends, homework, sleep), while, in a second step, we aimed to analyse the differences in socio-demographic characteristics (e.g. gender, socioeconomic status, smartphone ownership) and activities among these classes. The goodness of fit indices and inspection of unique characteristics within the classes pointed towards a four-class solution as the best choice (Table 1). Based on adolescents' responses on personal characteristics and online and offline activities, we identified a *social-recreational onliners*, a *weekend onliners,* a *balanced* and a *noninvolved* class, which are described in more detail hereafter.

[Table 1 about here]

Comparing the composition of the classes, several significant differences can be noticed and are described hereafter. Descriptives statistics of all the variables characterising the classes are collected in Table 2, together with post hoc test statistics reporting significant differences across classes. Additionally, Figures 1 and 2 include a graphical presentation of patterns of online and offline activities for each class.

[Table 2 about here]

[Figures 1 and 2 about here]

The *social-recreational onliners.* This class (n = 228 [21%]) consists of 65% females, with the majority of its members already owning their personal smartphone devices at T1 (95%). They also reported a slightly lower level of socioeconomic status compared to the *balanced* class and are the least likely to provide socially desirable answers. With regards to daily activities, this class shows the highest duration of time spent online: about half of its members (52%) declared to use the Internet for more than two hours on a typical school day, while the number of assiduous users grows up to 79% during weekend days. Similar results were found for the duration of smartphone use, meaning that members of this class primarily access the Internet through their personal mobile devices. *Social-recreational onliners* also reported being most frequently involved in social media activities (with "always" as the preferred response option), instant messaging, listening to music and watching online TV. Hence, being part of this class is primarily related to online activities targeting social experiences and entertainment contents. On the other hand, the Internet is less used for information search. Indeed, *social-recreational onliners* significantly differ from all the other classes only in the frequency of searching for information about celebrities and influencers (with "often" as the most chosen response option). Looking at patterns of offline activities, 70% of the members in this class declared to meet their friends for more than 2 hours a day, while almost half of them sleep fewer than the recommended number of hours for their age (8 to 10 hours). Compared to the *balanced* class, they also invest significantly less of their offline time in activities requiring higher levels of mental or physical effort, such as doing sport, homework or reading for fun.

The *weekend onliners.* The second class (n = 311 [28%]) is composed of 66% males. Like the *social-recreational onliners*, this class has a high penetration of smartphone ownership (95%). Furthermore, *weekend onliners* showed similar patterns of online activities, but an overall reduced duration of use. Although they invest almost the same amount of time on the Internet and/or with their smartphone during weekend days (with the most frequent answer option being "more than 2 hours"), half of the class spends less than 2 hours on their smartphone during a typical school day. Adolescents in this class also reported less social networking, chatting, watching online TV and listening to music than their more socially oriented counterpart, i.e. the *social-recreational onliners*. However, on average, they continue to perform social and entertainment-oriented online activities more often than the members of the *balanced* and the *noninvolved* class. Looking at patterns of offline activities, the *weekend onliners* spend significantly less of their offline time with friends but sleep more than the *social-recreational onliners*, while the time spent reading for fun remains equal. However, reading time significantly decreases compared to the *balanced* class, so does time for sleep.

The *balanced.* The third class (n = 404 [37%]) is made of 55% females and 83% smartphone owners. Compared to the *social-recreational onliners*, this class is characterised by higher average levels of socioeconomic status and social desirability responding. The *balanced* generally use the smartphone and the Internet less than the *social-recreational onliners*, with most of them reporting frequencies from "up to 1 hour" in a typical school day to "1 to 2 hours" during weekend days. With regards to their preferred online activities, response patterns converged towards a more homogeneous distribution across online TV and music entertainment, communication through instant messaging and school-related follow-ups. Interestingly, they rarely use social networks, online gaming, and search for gossip and games information compared to the more online-oriented groups (*social-recreational onliners* and *weekend onliners*). They also organise their daily offline activities in a more balanced way, dedicating more time to study and further diversifying their leisure activities. The majority of adolescents in this class spend 1 to 2 hours a day with friends and doing homework, saving more time to perform other activities such as reading for fun and playing sports (1 to 2 hours and more than 2 hours a day respectively). Finally, 86% of the members in this class reported sleeping for the recommended 8 to 10 hours a day.

The *noninvolved*. The fourth and final class (n = 153 [14%]) is mainly composed of males (56%), and only approximately half of them (53%) own a smartphone. Like the *balanced*, adolescents in this class showed to be significantly more prone to social desirability responding compared to the rest of the sample. They reported very low levels of online activities, with "never" as the preferred answer option during weekdays and "up to 1 hour" during weekend days. When connected to the Internet, the *noninvolved* primarily opt for passive entertainment, dedicating 1 to 2 hours a day watching online TV and listening to music. In the offline world, the majority reported a sufficient amount of sleep per day (8 to 10 hours). Despite little time with online activities, when compared to the *balanced* class, they also showed reduced levels of offline activities such as doing homework and sports.

Class membership and PSU

Our third and final research objective was to understand how class membership predicts PSU one year later. On average, *social-recreational onliners* had the highest level of PSU at T2 (M = 2.46, SD = 0.97) followed by the *weekend onliners* (M = 2.07, SD = 0.86), *noninvolved* (M = 1.84, SD = 0.85), and *balanced* (M = 1.80, SD = 0.75) class.

To predict PSU by class membership, we regressed PSU at T2 on class membership, controlling for gender as well as PSU, socioeconomic status, social desirability, and smartphone ownership at T1. The latent class regression model explained 16% of the variance in the outcome variable [$F(8,1087) = 26.45$, $p < .001$]. Considering the *social-recreational onliners* class as the reference group, the results indicate that being part of any of the other classes at T1 predicts significantly lower levels of PSU at T2 (Table 3). Significant mean differences in PSU levels at T2 were, in fact, present when compared to the *weekend onliners* (B = -0.22, p = .003), *balanced* (B = -0.31, p < .001), and *noninvolved* class (B = -0.30, p = .002). After changing the reference group, no significant differences in PSU at T2 were evident between the *weekend onliners*, the *balanced*, and the *noninvolved* class.

As expected, PSU at T1 significantly positively predicts PSU one year later (B = 0.34, p < .001). Furthermore, among the covariates, only social desirability has a significant negative effect on our outcome variable of interest (B = -0.09, p = .037), meaning that a higher propensity to provide socially desirable answers at T1 produced lower levels of self-reported PSU at T2.

[Table 3 about here]

Discussion

The study of problematic smartphone use (PSU) among adolescents is of great importance to understand what behavioral dynamics are introduced by new technologies and which are the possible health-related consequences. In this study, we used two-wave panel data and applied latent class regression analysis as an exploratory approach to identify classes of adolescents based on their patterns of online and offline activities and to predict differences in their PSU levels one year later.

We identified four distinct classes: the *social-recreational onliners*, the *weekend onliners*, the *balanced* and, finally, the *noninvolved*. The former class is made up of the most frequent Internet and smartphone users. Almost all (95%) of them own a personal smartphone device and they use it mainly for social networking, instant messaging and a series of leisure purposes such as listening to music, watching online TV and searching for gossip news. Their considerable involvement in social and recreational activities is accompanied by higher investment in offline relationships with friends and a significant reduction of sleep compared to the other three classes. The *weekend onliners* also own a smartphone in 95% of the cases, and they show similar patterns of online activity to those of the *social-recreational onliners*. However, what changes between the two is the overall amount of time spent with the smartphone in everyday life. In fact, *weekend onliners* reported to use the device less frequently during weekdays, showing a reduced overall investment in online social networking and digital media consumption. Furthermore, they engage less frequently in offline peer relationships and have an increased daily average sleep time. Differences in online and offline activities are even more evident when comparing the *social-recreational onliners* to the *balanced* and the *noninvolved* class. They respectively reported smartphone possession rates at T1 equal to 83% and 53%, accompanied by a significant reduction in the time spent on the Internet and with friends throughout the whole week. If both classes showed a general increase in sleep time, members of the *balanced* class invest more time than the *social-recreational onliners* in other offline activities, such as reading for fun, playing sports and doing homework.

Besides variations in the patterns of online and offline activities, the four classes show other relevant peculiarities that deserve to be mentioned. Looking at the differences in their socio-demographic characteristics, females represent the majority of the *social-recreational onliners*. This evidence is in line with representative national survey data on social media use, showing that girls are more active on social media platforms and in messenger services than their male counterparts (Pew Research Center, 2018; Süss et al., 2018). While the share of adolescents with less socioeconomic resources was also higher in the *social-recreational onliners* class, a significant difference was only evident in comparison to the *balanced* class and, thus, should be interpreted with caution. In fact, data from the US and Switzerland showed no considerable differences in adolescents' smartphone use as well as their use of YouTube and Instagram as the most favourite online platforms, dependent on their socioeconomic background (Pew Research Center, 2018; Süss et al., 2018).

Finally, we explored the distribution of a measure of social desirability across the four classes. This issue becomes particularly relevant in light of the results that emerged from previous research, which underlined that respondents tend to underreport about symptoms of problematic Internet and smartphone use (Mok et al. 2014; Montag et al. 2010). As expected, the distribution of social desirability proneness was inversely related to the overall amount of time spent on the Internet and using the smartphone, which emphasises the need to control for respondents' disposition towards socially desirable response patterns throughout the study.

Turning to the analysis of the impact of latent class membership on PSU measured one year later, our findings highlight the presence of significant differences across the classes. Independent from their gender, socioeconomic status, smartphone ownership, and the propensity to social desirability responding, *social-recreational onliners* showed the highest perceived levels of PSU measured at a one-year distance, followed by the *weekend onliners,* the *noninvolved*, and the *balanced* class. However, the latter three classes do not significantly differ from each other. Thanks to the autoregressive nature of our model, these results can be attributed to the specific patterns of online and offline activities registered for the *social-recreational onliners*.

Significantly higher levels of perceived PSU over time in *social-recreational onliners* are mainly the consequence of their online activities characterised by longer time spent online and higher engagement in social networking and online entertainment activities. This result adds new longitudinal evidence on the relationship between specific types of media consumption, i.e. entertainment- and social media-oriented, and personal well-being, suggesting that substantial investment in such activities is not only cross-sectionally associated with smartphone overuse and related adverse health outcomes (Jeong et al., 2016; Salehan and Negahban, 2013; van Deursen et al., 2015; Zhitomirsky-Geffet and Blau, 2016), but also to higher PSU levels over time.

It is also important to recall that variations in online social networking activities registered among the *social-recreational onliners* go hand in hand with the daily amount of time members of this class spend cultivating offline social connections. This result stands in contrast to the widespread idea that individuals flee to intensive online social networking mainly to shy away from feelings of loneliness and uneasiness toward offline interactions (e.g., Chiu, 2014; Griffiths et al., 2014; Ihm, 2018; Kuss et al., 2018). Instead, it seems that social networks and instant messaging services represent additional tools exploited by the most outgoing and sociable individuals to maintain, complement and/or expand their social connections (Ihm, 2018; Raine and Wellman, 2012). In general, meeting friends in person is primarily motivated by the need to reinforce bonds of reciprocal support, to actively contribute to the enhancement of acceptance and approval by others, and to increase the leisure opportunities in the shared community, all needs which are of great importance during adolescence. Online social services offer the same opportunities (Cheung et al., 2011). However, they also increase the duration of smartphone use and foster its pervasiveness towards other life domains (Jeong et al., 2016; Kuss et al., 2018; Salehan and Negahban, 2013). Almost all current social network services are now developed into mobile-based environments, and smartphones have become the main device for social networking and instant messaging (Goggin, 2014). Due to its portability and connectivity, the device provides a platform for users to constantly access social networks regardless of time or space boundaries, favouring the consolidation of frequent checking habits (Oulasvirta et al., 2012) and its use in the meanwhile of doing other activities (Hwang et al., 2014; Jeong and Fishbein, 2007). Moreover, the business model behind mobile social networks pushes developers to systematically exploit users' attention by implementing hooking stimuli based on instant feedback and social rewards that are hard to resist (Eyal, 2014; Seaver, 2018). For all these reasons, social networking and online messaging as 'social' or 'process-oriented' activities are considered among the strongest predictors of PSU, even more than other well-known addictive activities such as online gaming (Jeong et al., 2016; Song et al., 2004). Thus, from a theoretical point of view, the findings of this study provide support for the UGT, which states that people may seek gratifications from competing online *and* offline sources, though offline sources were not covered in past studies on PIU/PSU. However, these sources do not necessarily compete with but complement each other. In fact, more time spent with offline friends also reflects in higher reported usage of the Internet and the smartphone for social activities as an integrative form of social interactions. The repeated engagement in online social (and recreational) activities can become problematic due to the way in which mobile social media push users towards repeated and compulsive online activities that facilitate the occurrence of PSU (Oulasvirta et al., 2012).

An additional finding of the present study that deserves discussion is related to differences in the duration of other offline activities. For example, the *social-recreational onliners* reported a significantly lower sleep time than any other class. This evidence aligns with past studies reporting that prolonged exposure to the smartphone can interfere with the circadian rhythm, negatively affecting sleep duration and quality (Christensen et al., 2016; Lemola et al., 2015). This can be particularly the case of adolescents, considering that almost 50% of them declare to spend time with the smartphone in the bedroom and 25% claim to use the device at night (Graafland, 2018; Gui et al., 2018). Other studies underlined that a longer duration of smartphone use (and the Internet in more general) go to the detriment of sleep, which is required to stay concentrated in class and during homework (Carter et al., 2016; Hale and Guan, 2015). Indeed, compared to the *balanced* class, *social-recreational onliners* are less involved in other types of offline activities requiring higher mental and physical effort, such as doing homework, doing sports or reading books. However, comparing the distribution of these activities with the remaining two classes, their patterns are similar to those of the *weekend onliners* and the *noninvolved*, who both report lower levels of PSU, meaning that adolescents' lower disposition towards these cognitively and physically engaging activities does not actively contribute to higher levels of PSU one year later.

To sum up, we found that increased PSU over time is related to smartphone use during weekdays for social and recreational purposes, taking into account socio-demographic characteristics and initial gaps in the access to the device and potential biases in social desirability responding. We also found that smartphone use for such purposes is positively linked to the amount of time spent offline by adolescents in the company of friends. These results suggest that dispositional differences across individuals could lead them to develop particular needs to be gratified and, in turn, such needs could influence their choices in consuming media (e.g., Elhai and Contractor, 2018; Wang et al., 2012). However, meeting these needs can become problematic. To avoid the emergence or overcome maladaptive behavioral patterns, recent experimental studies suggested investing in media education initiatives primarily aimed at fostering adolescents' self-regulation skills through the development of shared best practices (Gui et al., 2018). The results of these studies highlight how the simple establishment of one or more relevant moments of the day, during which the smartphone should be turned off or put in silent mode (e.g., during family mealtime, while doing homework or sleeping), effectively helps adolescents in reducing its pervasiveness and perceived problematic use. Working on self-monitoring strategies can effectively reduce PSU, eventually contributing to the enhancement of individuals' relational well-being.

Limitations and future directions

The present study provides new insights on online (including smartphone-related) and offline activities among adolescents and how these contribute to increases in PSU over time. As such, it overcomes many limitations reported in other studies applying latent class analysis, which rely on cross-sectional data and student samples to study the phenomenon of addictive or problematic smartphone use (e.g., Elhai and Contractor, 2018). However, some limitations need to be acknowledged. First, we relied on self-reports, which are subject to different biases. Although we controlled for social desirability bias, other biases related to time estimation and recall might still affect the findings (Slater, 2004). Thus, we suggest that future studies should include ecological momentary assessments and trace data to overcome these biases and give a more objective and reliable picture of adolescents' online and offline activities and how they contribute to adverse outcomes, including the development of PSU. Using smartphone trace data in an adult population, Wilcockson and colleagues (2018) found that automatically recorded usage and checking behaviors were unrelated to self-report PSU. This finding underlines that the time component is not a sufficient predictor of PSU, but more research with larger samples is needed to provide further evidence. In addition, a content-specific automated assessment of smartphone or Internet use would give even more insights on what patterns of actual use predict PSU. However, automated content-specific tracking (e.g., usage broken down by applications) are challenging given the technical limitations and ethical consideration, especially in underage populations (Stier et al., 2019). Second, we categorised individual online activities in terms of duration per weekday and weekend day. However, the frequency might be an additional informative predictor of PSU as some activities come along with shorter yet more scattered and pervasive smartphone use, i.e., repeated checking of incoming messages or social media posts in the presence of others, while other activities are practised in longer sittings in more privatised settings, i.e., watching a series on a streaming platform. Thus, future studies should explore if the frequency of smartphone use may differ for single online activities and eventually impact PSU over time. Once again, more objective measures such as trace data present a valid alternative to self-report, especially in the context of high frequency daily online activities. Third, we only considered a small selection of online and offline activities. Although the selected activities reflect the heterogeneity of daily routines, the questions did not comprehensively assess the domains considered. Further studies should include a more detail assessment of, for example, the type of physical activity and the activities done in the company of friends. Additionally, the assessment of online activities can be further broken down by considering the type of platform used (e.g., single social media platforms) and the format of the information searched (e.g., videos, pictures). Fourth, although we used two-wave panel data and modelled autoregressive effects, we could not differentiate between an *inter*-individual and *intra*-individual change in PSU over time. The latter requires random-effects models (Bell et al., 2019; Selig and Little, 2012).

Despite these shortcomings, the present study demonstrates that the urgency to gratify needs of social enhancement, interpersonal connectedness, and entertainment through online and, more specifically, smartphone-related activities leads to higher levels of problematic smartphone use. This highlights the importance of efforts aimed at behavior change to balance offline and online activities effectively.

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Conflict of Interest

None declared.

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Table 1. Fit indices for different latent class models

Model (n of classes)	log-likelihood	*df*	BIC	SABIC	cAIC	likelihood-ratio	Entropy
Model 1 (2)	-23143.38	979	47105.68	46734.06	47222.68	30955.09	0.897
Model 2 (3)	-22730.11	919	46699.11	46136.92	46876.11	30134.02	0.808
Model 3 (4)	**-22438.19**	**859**	**46535.24**	**45782.48**	**46772.24**	**29568.64**	**0.848**
Model 4 (5)	-22225.98	799	46530.78	45587.44	46827.78	29355.61	0.811
Model 5 (6)	-22010.59	739	46519.98	45386.07	46876.98	28919.37	0.765

Table 2. Person characteristics, online activities and offline activities, and PSU by latent class membership

	Overall sample (N = 1,096)	Social-recreational onliners (N = 228) (*A*)	Weekend onliners (N = 311) (*B*)	Balanced (N = 404) (*C*)	Noninvolved (N = 153) (*D*)	Dunn-Bonferroni test (p < .05) *AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Female $^{\alpha}$	574 (52%)	149 (65%)	136 (44%)	221 (55%)	68 (44%)	*AB*		*AD*	*BC*		
Perceived SES $^{\gamma}$	2.8 (0.7)	2.7 (0.8)	2.8 (0.7)	2.9 (0.7)	2.8 (0.8)		*AC*				
Smartphone ownership $^{\alpha}$	929 (85%)	217 (95%)	296 (95%)	335 (83%)	81 (53%)		*AC*	*AD*	*BC*	*BD*	*CD*
Social desirability $^{\gamma}$	3.2 (0.6)	2.9 (0.7)	3.2 (0.6)	3.4 (0.5)	3.4 (0.6)	*AB*	*AC*	*AD*	*BC*	*BD*	
Online activities (T1)											
Smartphone (week day) $^{\beta}$	2 (2-3)	4 (3-4)	3 (3-3)	2 (2-2)	2 (1-2)	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Smartphone (weekend day) $^{\beta}$	3 (2-4)	4 (4-4)	4 (3-4)	3 (2-3)	2 (1-3)		*AC*	*AD*	*BC*	*BD*	*CD*
Internet (week day) $^{\beta}$	2 (2-3)	4 (3-4)	3 (3-3)	2 (2-2)	2 (1-2)		*AC*	*AD*	*BC*	*BD*	*CD*
Internet (weekend day) $^{\beta}$	3 (2-4)	4 (4-4)	4 (3-4)	3 (2-3)	2 (2-2)		*AC*	*AD*	*BC*	*BD*	*CD*
Internet for TV $^{\beta}$	3 (2-4)	4 (3-4)	3 (3-3)	3 (2-3)	2 (2-3)	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Internet for information seeking $^{\beta}$	2 (2-3)	2 (2-3)	2 (2-3)	2 (2-3)	2 (1-2)			*AD*		*BD*	*CD*
Internet for gaming $^{\beta}$	2 (1-3)	2 (1-3)	2 (1-3)	2 (1-2)	1 (1-2)		*AC*	*AD*	*BC*	*BD*	
Internet for music $^{\beta}$	3 (2-4)	4 (4-4)	3 (3-4)	3 (2-3)	2 (1-3)	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Internet for social network $^{\beta}$	2 (1-3)	4 (3-4)	3 (2-3)	2 (1-3)	1 (1-1)	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Internet for school $^{\beta}$	2 (2-3)	2 (1-3)	2 (2-2)	2 (2-3)	2 (1-2)		*AC*	*AD*	*BC*	*BD*	*CD*
Internet for messaging $^{\beta}$	3 (2-4)	4 (4-4)	3 (3-4)	3 (2-3)	2 (1-2)	*AB*	*AC*	*AD*	*BC*	*BD*	*CD*
Internet for news $^{\beta}$	2 (1-2)	2 (1-3)	2 (1-2)	2 (2-2)	1 (1-2)			*AD*		*BD*	*CD*
Internet for gossip $^{\beta}$	2 (1-3)	3 (2-3)	2 (2-3)	2 (2-3)	1 (1-2)	*AB*	*AC*	*AD*		*BD*	*CD*
Internet for health $^{\beta}$	1 (1-2)	1 (1-2)	2 (1-2)	2 (1-2)	1 (1-1)			*AD*		*BD*	*CD*
Internet for games information $^{\beta}$	2 (1-3)	2 (1-3)	2 (1-3)	2 (1-2)	1 (1-2)		*AC*	*AD*	*BC*	*BD*	
Offline activities (T1)											
Sport $^{\beta}$	3 (2-4)	3 (2-4)	3 (2-3)	3 (2-4)	3 (2-3)		*AC*				*CD*
Reading books $^{\beta}$	2 (2-2)	2 (1-2)	2 (2-2)	2 (2-2)	2 (2-2)		*AC*		*BC*		
Friends $^{\beta}$	3 (2-4)	4 (3-4)	3 (3-4)	3 (2-4)	3 (2-4)	*AB*	*AC*	*AD*	*BC*	*BD*	
Homework $^{\beta}$	3 (2-3)	2 (2-3)	3 (2-3)	3 (2-3)	2 (2-3)		*AC*				*CD*
Sleep $^{\beta}$	3 (2-3)	2 (2-3)	3 (2-3)	3 (3-3)	3 (3-3)	*AB*	*AC*	*AD*	*BC*	*BD*	
Problematic smartphone use (T1) $^{\gamma}$	1.8 (0.7)	2.3 (0.8)	1.9 (0.7)	1.9 (0.7)	1.5 (0.8)	*AB*	*AC*	*AD*	*BC*	*BD*	
Problematic smartphone use (T2) $^{\gamma}$	2.0 (0.9)	2.5 (1.0)	2.1 (0.9)	2.1 (0.9)	1.8 (0.8)	*AB*	*AC*	*AD*	*BC*	*BD*	

$^{\alpha}$ Categorical variable: frequency and percentage in brackets;
$^{\beta}$ Ordered categorical variable: median and first-third quartiles in brackets;
$^{\gamma}$ Continuous variable: mean and standard deviation in brackets.

Table 3. Multiple regression model predicting PSU at T2

Predictors at T1	***B***	**S.E.**	***t***	***p***
Female	-0.010	0.050	-0.201	.841
SES	-0.054	0.033	-1.625	.104
Social desirability	-0.090	0.043	-2.085	.037
Smartphone ownership	-0.030	0.074	-0.400	.689
Problematic smartphone use	0.338	0.038	8.918	<.001
Intercept (Class A, social-recreational onliners)	2.111	0.210	10.029	<.001
Class B (weekend onliners)	-0.216	0.073	-2.947	.003
Class C (balanced)	-0.309	0.077	-4.022	<.001
Class D (noninvolved)	-0.303	0.097	-3.131	.002
Intercept (Class B, weekend onliners)	1.894	0.209	9.046	<.001
Class C (balanced)	-0.093	0.064	-1.433	.152
Class D (noninvolved)	-0.087	0.087	-0.995	.320
Intercept (Class C, balanced)	1.802	0.208	8.647	<.001
Class D (noninvolved)	0.005	0.080	0.069	.945

Adjusted R^2=.157, F(8,1087)=26.45, p<.001. The analysis was repeated for each reference group. Only additional comparisons are shown.

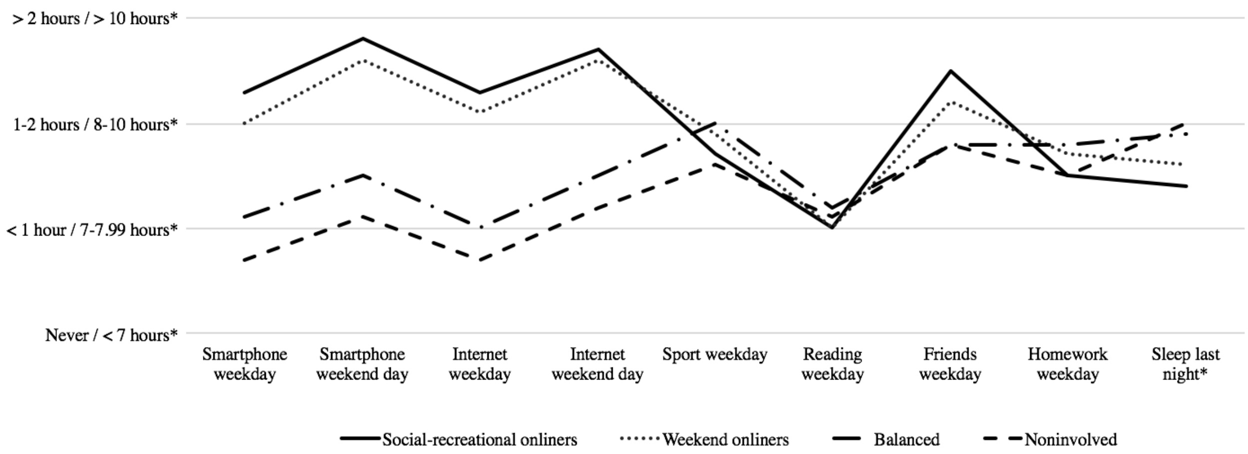

Figure 1. Patterns of overall online and offline activities by latent class membership

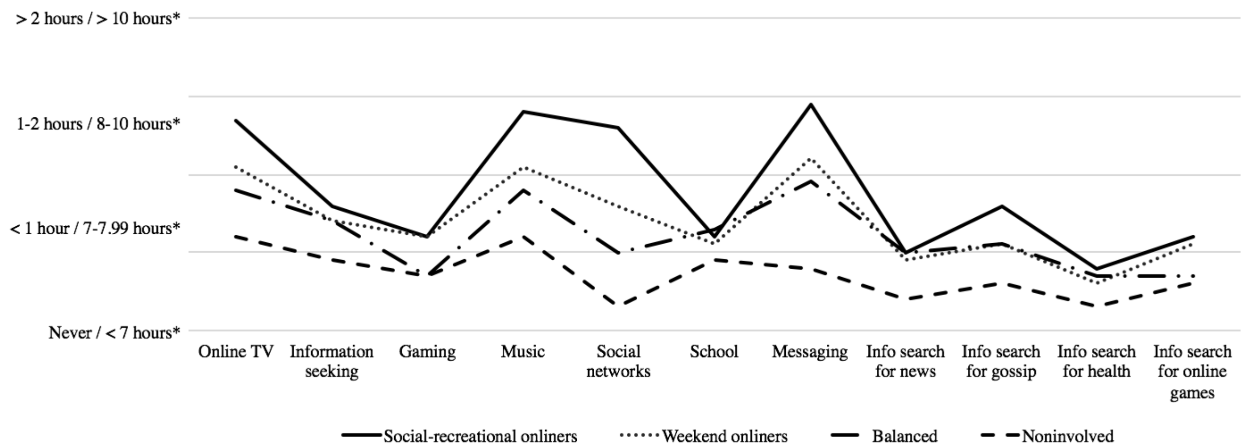

Figure 2. Patterns of specific online activities by latent class membership

Appendix A

Variable label	Question	M	SD	Median	1Q	3Q
Internet for TV	How often do you use the Internet to watch TV programmes or videos? (e.g. YouTube, Zattoo…)	2.99	0.83	3.00	2.00	4.00
Internet for information seeking	How often do you use the Internet to search for information (e.g., Wikipedia, Google, Yahoo Answer, FocusJunior, ...)?	2.36	0.80	2.00	2.00	3.00
Internet for music	How often do you use the Internet to listen to music (e.g., Soundcloud, Youtube, iTube, ...)?	3.00	0.89	3.00	2.00	4.00
Internet for social network	How often do you use the Internet for social networking activities (e.g., Facebook, Twitter, Instagram, ...)?	2.42	1.14	2.00	1.00	3.00
Internet for school	How often do you use the Internet to do research for school?	2.17	0.79	2.00	2.00	3.00
Internet for messaging	How often do you use instant messaging applications?	3.01	0.93	3.00	2.00	4.00
Internet for news	How often do you search for news on the Internet?	1.89	0.77	2.00	1.00	2.00
Internet for gaming	How often do you use the Internet for online gaming (es: Final Fantasy, World of Warcraft, ...)?	1.95	1.00	2.00	1.00	3.00
Internet for health	How often do you search for health information on the Internet?	1.63	0.76	1.00	1.00	2.00
Internet for games information	How often do you search online gaming information on the Internet?	1.92	0.99	2.00	1.00	3.00
Internet (weekday)	During a typical weekday, out of school, how often do you use the Internet?	2.55	0.86	2.00	2.00	3.00
Internet (weekend)	During a typical weekend day, how often do you use the Internet?	3.01	0.85	3.00	2.00	4.00
Smartphone (weekday)	During a typical weekday, out of school, how often do you use the smartphone?	2.55	0.91	2.00	2.00	3.00
Smartphone (weekend)	During a typical weekend day, how often do you use the smartphone?	3.03	0.90	3.00	2.00	4.00
Reading books	During a typical weekday, out of school, how often do you read a book for fun?	2.07	0.77	2.00	2.00	2.00
Friends	During a typical weekday, out of school, how often do you spend time with friends?	3.06	0.97	3.00	2.00	4.00
Homework	During a typical weekday, out of school, how often do you do the homework	2.67	0.74	3.00	2.00	3.00
Sleep	Sleep duration calculated from: When did you go to sleep last night? and When did you get up this morning?	2.73	0.64	3.00	2.00	3.00

Note: Answer format for activities reported in the "Measures" section of the article; 1Q = 1st quartile, 3Q = 3rd quartile