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Heterogeneity of smartphone impact on everyday life and its relationship with personality and psychopathology: A latent profile analysis

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ABSTRACT

Background: The relationships between problematic smartphone use and psychological factors have been extensively investigated. However, previous studies generally used variable-centered approaches, which hinder an examination of the heterogeneity of smartphone impact on everyday life.
Objective: In the present study, we capitalized on latent profile analysis to identify various classes of smartphone owners based on the impact associated with smartphone use (e.g., unregulated usage, preference for smartphone-mediated social relationships) and to compare these classes in terms of established psychological risk factors for problematic smartphone use.
Method: We surveyed 934 young adults with validated psychometric questionnaires to assess the impact of smartphones, psychopathological symptoms, self-esteem and impulsivity traits.
Results: Smartphone users fall into four latent profiles: users with low smartphone impact, users with average smartphone impact, problematic smartphone users, and users favoring online interactions. Individuals distributed in the problematic smartphone user profile were characterized by heightened psychopathological symptoms (stress, anxiety, depression, obsessive-compulsive tendencies) and impulsivity traits. Moreover, users who preferred online interactions exhibited the highest symptoms of social anxiety and the lowest levels of self-esteem.
Conclusions: These findings further demonstrate the multidimensionality and heterogeneity of the impact of smartphone use, calling for tailored prevention and intervention strategies.

Smartphones have become essential for most people in everyday life by helping them to communicate with other individuals and groups (e.g., instant messaging services, oral communication, social networking), organize work and activities, and enjoy entertainment (e.g., video gaming, streaming). Despite the many benefits of smartphones, certain forms and levels of use have been associated with poorer health and well-being [31,32,43,89]. Yet, the potential risks and consequences linked with problematic or "deregulated" use of smartphones remain a highly debated topic [15]. Nonetheless, existing evidence suggests that problematic smartphone use (PSU; variously named compulsive smartphone use, smartphone addiction, smartphone use disorder; see [66]) holds public health implications [107]. PSU has generally been defined as a compulsive pattern of smartphone usage associated with significant impairment across multiple domains of individual functioning (e.g., compromised social relationships, impeded user productivity, physical health, or emotional well-being in daily life) that is characterized by addiction-like symptoms such as loss of control or withdrawal [34,43].

Despite the various types of impact of smartphone use on everyday lives (e.g., unregulated usage, preference for smartphone-mediated social relationships), research examining the co-occurrence and relationships between these impacts is still scarce. Examining the extent to which these impacts coexist, as well as their associations with known risk factors for PSU severity (e.g., personality-related measures and psychopathological symptoms), may provide essential information that

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would contribute to a better understanding of the process by which certain forms and levels of smartphone use might turn into problematic behavior. The aim of the present study was thus to identify profiles of smartphone users according to different types of smartphone impact and to compare these profiles in terms of PSU-relevant personality and psychopathological variables.

1. The dynamic interplay of smartphone impact

Most of the recent studies on the impact of smartphone use have examined associations between PSU severity and psychopathology/personality by using a variable-centered approach, which allowed for the study of relationships between variables. However, some scholars have highlighted the limits of this approach (e.g., [30,31,110]). In particular, a variable-centered approach hinders the consideration of variable interrelationships for specific individuals (i.e., a subgroup of participants among a sample), thus failing to provide any information about person-specific characteristics and behaviors. An alternative approach would involve a person-centered approach, which focuses on the individual level rather than on the variable level [30,31,110]. Latent profile analysis (LPA) is a person-centered analysis that allows one to take into account the heterogeneity of a target group by clustering participants' item responses into mutually exclusive classes or profiles (e.g., individuals with similar symptoms of a disorder; [53,71]).

Recently, researchers in the PSU field have begun to adopt a person-centered approach, with the aim of identifying different clusters of smartphone users based on their symptom profiles. For example, a series of studies conducted in Korea identified classes of problematic Internet and smartphone users from the total score on scales that measured problematic usage patterns [50,56,65]. In recent years, a growing number of studies have aimed to empirically investigate the heterogeneity of smartphone users' profiles by using a symptom-based score (item-level data) rather than by considering only a global (or total) score obtained on scales that measure problematic usage patterns. In a study involving 300 American college students, Elhai and colleagues [,30] found support for a three-class model of latent groups of individuals based on their answers on a scale assessing various PSU symptoms (10 different symptoms were considered in the latent class analysis). Capitalizing on such an approach, the authors found that individuals incorporated in classes characterized by moderate and severe symptoms reported significantly higher levels of anger and worry. Furthermore, in a subsequent study conducted on 286 American college students divided into two classes on the basis of 10 different symptoms of PSU, Elhai et al. [31] demonstrated that more severe symptoms (including pronounced withdrawal) were associated with increased rumination and negative smartphone use expectancies (e.g., to relieve stress). In another study, Yue et al. [110] recruited 539 college students in Inner Mongolia and found three latent classes of smartphone users by using the same approach and same scale as Elhai et al. did [30,31]. They showed that users in classes characterized by more marked PSU symptoms displayed heightened emotional symptoms (severity of depression, social anxiety, and boredom). Some similarities characterize the classes identified in these previous studies. More specifically, severe/high-risk classes presented with higher withdrawal-like symptoms (e.g., being impatient/fretful when deprived of the smartphone, thinking to use the smartphone when separated from it) in comparison to the mild/less-risk classes, whereas a smaller range of differences across classes was shown for other aspects, such as impact on work. Notably, however, these three studies all capitalized on the Smartphone Addiction Scale (SAS)—Short Version [52], which measures only one type of smartphone impact: the addictive use of the smartphone (e.g., tolerance, withdrawal, preoccupation). Such an approach has been criticized because it ignores other types of potential impacts of smartphone use, beyond mere addictive usage [9,77]. Furthermore, considering only the addiction perspective risks to neglect other potentially important impacts of the smartphone. In this context, and with the aim of broadening the scope of assessment of smartphone impact, Pancani et al. [77] recently developed a comprehensive and psychometrically valid instrument (the Smartphone Impact Scale [SIS]) that comprises various cognitive (e.g., awareness about the possible adverse consequences of smartphone use), affective (e.g., smartphone use to cope with negative inner states), social (e.g., smartphone use as a means of maintaining romantic and friendship relationships), and behavioral (e.g., smartphone overuse) impacts of smartphones on everyday life. The SIS is thus a conceptually and methodologically sound scale for investigating the heterogeneity of the impact of smartphone use [77]. For example, by capitalizing on the SIS, it is possible to identify profiles of smartphone users with high levels on those dimensions that are more closely related to PSU severity (e.g., loss of control, nomophobia, and emotion regulation) but without increased rates on other dimensions; profiles presenting with an overall PSU (i.e., affecting all types of impacts assessed); or, in contrast, profiles characterized mainly by positive smartphone impacts (i.e., usage supporting romantic relationships and daily activities) and awareness regarding its potential negative impact in case of overuse.

2. Psychological risk factors for PSU

According to several systematic reviews (e.g., [15,27,96]), PSU is associated with specific psychopathological symptoms and personality characteristics. The Interaction of Person-Affect-Cognition-Execution (I-PACE) model [12,13] is useful to account for the associations between these different variables and their relationships with PSU manifestations. This model posits that excessive smartphone use (and more largely excessive technology-mediated behaviors) can be conceptualized as genuine addictive behaviors. This model describes a two-stage process, whereby the technology-mediated addictive behavior is first and primarily driven by general predisposing factors that have been linked to the onset and development of addictive behaviors in previous research [45,91]. These personal characteristics include psychopathological symptoms (e.g., depression, social anxiety) and temperamental features (e.g., self-esteem, impulsivity). Individuals may excessively use their smartphones in an attempt to cope with adverse emotional states and to compensate for real-life stressors or unmet needs, for instance, by using specific smartphone apps [92] or by connecting on social networking sites to seek social support [58]. Previous research showed moderate associations between PSU severity and depression symptoms [27], as well as small-to-moderate associations with anxiety and stress [27,29,96], which has been interpreted as reflecting a compensatory mechanism, such as the smartphone being used to regulate negative affect. Other studies have shown positive associations between the severity of social anxiety and PSU symptoms, suggesting that socially anxious users might prefer smartphone-mediated communication over face-to-face interactions (e.g., [33,114]). Thus, social anxiety is considered within the I-PACE model as a clinical variable that puts individuals at higher risk of developing addictive patterns of technology use as a means of compensating for their social deficits [38]. Regarding the temperamental features, poor self-esteem was related to PSU severity, signifying that individual differences in the confidence in one's own worth or abilities are likely to play a role in the emergence of PSU-related symptoms [51]. As indicated in a recent meta-analysis on the association between self-esteem and PSU [20], individuals with a negative evaluation of self may preferentially use their smartphones to maintain or increase their self-esteem through the feedback received from others. Furthermore, individuals with low self-esteem may develop a preference for smartphone-mediated communication, ultimately leading to PSU, as this may constitute a useful alternative to maintaining interpersonal relationships while minimizing the discomfort that they typically experience in face-to-face interactions [23]. The personality trait of impulsivity, which entails the tendency to act rashly or without adequate forethought, with difficulty in delaying reward, and reduced inhibition capacity [104], was consistently associated with PSU symptoms in previous studies [16,40,46]. As explained by Mitchell and Hussain [64], individuals with high impulsivity present with proneness to fail to control urges to use their smartphones, for instance, by checking their notifications, which can increase unregulated smartphone use and its associated negative consequences.

Crucially, as specified in the I-PACE model [12,13], the development of a problematic behavior occurs in the interaction between specific predisposing variables and certain aspects of the environment. In the case of smartphone use, high availability and accessibility are likely to promote overuse (e.g., using multiple potentially time-consuming applications on the same device, constantly receiving notifications), thanks to certain predisposing variables and reinforcement processes related to a wide range of gratifying content [76]. In a subsequent stage, the combination of self-control and executive impairment, together with conditioning processes, translates into compulsive behaviors promoted by the easy availability of the smartphone [39]. These compulsive patterns of use are suggested to mainly act as negative reinforcement processes (e.g., to regulate mood and avoid negative emotions, distract oneself from difficulties, and be constantly online and available to others). The shift from impulsivity to compulsivity is a key component of many addictive disorders [14] and a similar shift may thus occur in the context of PSU [57].

Although PSU is generally defined as the unregulated use of the device, which may at least partly derive from compulsive checking [93], the study of the association between obsessive-compulsive disorder (OCD) symptoms and PSU symptoms has received little attention to date. The first studies having explored such a link found OCD symptoms to be correlated with PSU severity in various samples and regions [4,35,55]. Another study, however, did not reproduce this finding in a sample of Lebanese adults [73]. Of note, given that the nature and content of specific obsessions and compulsions are affected by cultural, social, and technological influences, it has been argued that technology may influence the nature and form of OCD symptoms linked to technology use ("digital symptoms"; see [19]). For instance, compulsive checking may be performed through technological devices, resulting in various behaviors (e.g., collections of apps, repeated and uncontrolled checks of social network apps, constant verification of e-mails). The apps may also be compulsively checked to make sure they open or close "properly," or that messages/icons were sent in the "right" manner or time [93]. Notably, case reports of social media and smartphone technology in OCD symptoms have been described, for example, a patient checking her smartphone compulsively to verify whether she had posted an inappropriate or shameful reaction or an icon (see [98]). Other research showed that problematic use of video games or social media is positively associated with OCD symptoms [1]. Moreover, in a study focusing on problematic Internet use, two impulsive-compulsive domain variables (i.e., hoarding and obsessing symptoms) have been found to be positively linked to the severity of the problematic behavior [68]. In this study, hoarding showed higher power to statistically predict problematic use severity and greater accuracy to identify individuals with versus without Internet use-related problems. Previous studies argued that digital hoarding, which entails the accumulation of digital information to the point of loss of perspective, can be a key aspect in technology-related problematic behaviors [95,97]. However, research is warranted to better understand the association between OCD symptoms and PSU severity.

3. The present study

To the best of our knowledge, no study has yet identified subgroups of smartphone users by taking a multidimensional approach to the impact of smartphone use and its relationships with established risk factors for PSU. Indeed, previous studies essentially focused on addictive usage patterns. In the current study, we thus aimed to use LPA to identify and define subtypes of smartphone users based on individual responses obtained from the SIS [77].

We also aimed to establish the validity of the profiles obtained through their associations with relevant external correlates, i.e., variables not used in profile generation that are established risk factors to account for PSU severity, including impulsivity traits and psychopathological symptoms. More specifically, we aimed to explore how different subtypes of smartphone users differ in terms of these external correlates. We expected the various classes (or profiles) to differ according to these external correlates, with the most problematic profiles being characterized by heightened impulsivity traits, low self-esteem, and more marked psychopathological symptoms (general and social anxiety, depression, stress, and obsessive-compulsive symptoms).

4. Method

4.1. Participants and procedure

A cross-sectional design was used with an online survey completed by a convenience sample recruited through advertisements on local online messaging boards and social networking site groups of the University of Padova. The advertisements specified that the study targeted college students. Only participants aged 18–35 years and who were fluent in Italian were retained in the study. Participants were requested to complete an online survey (available from June 13 to October 15, 2019) and informed that the study aimed to increase scientific knowledge about PSU in college students. All participants gave their online informed consent before starting the survey, and anonymity was guaranteed. It took approximately 30 min to complete. A total of 1397 participants responded to the questionnaire, of whom 187 were excluded because they provided inconsistent responses on all four items intended to identify careless answering (item example: "click now on number 3"). For the purpose of the current study, participants who did not complete any of the SIS items ($n = 239$) were excluded. Moreover, participants younger than 18 years or older than 35 ($n = 37$) were also excluded. Therefore, the analyses were performed on a final sample of 934 Italian-speaking young adults whose demographic characteristics are presented in Table 1. The study protocol was approved by the ethical committee for the Psychological Research of the University of Padova (research registration number: 3104). This study was part of a larger

Table 1
Descriptive statistics of the sample.

Sociodemographic Characteristics	Statistics	
Age	$M = 23.96$	$SD = 3.09$
Gender		
Males	$n = 287$	30.7%
Females	$n = 645$	69.1%
Not declared	$n = 2$	0.2%
Student working status		
Permanent, full time	$n = 95$	10.2%
Fixed term, full time	$n = 79$	8.5%
Permanent, part time	$n = 51$	5.5%
Fixed term, part time	$n = 149$	16.0%
Not working	$n = 560$	60.0%
Relationship		
Single	$n = 307$	32.9%
Casually date	$n = 44$	4.7%
In a committed relationship	$n = 548$	58.7%
Married	$n = 12$	1.3%
Divorced	$n = 3$	0.3%
Not declared	$n = 20$	2.1%
Living place		
Student residence	$n = 29$	3.1%
College	$n = 11$	1.2%
Parents' house	$n = 473$	50.6%
House for rent, with other students	$n = 250$	26.8%
House for rent, alone	$n = 71$	7.6%
Other	$n = 77$	8.2%
Not declared	$n = 23$	2.5%

Note. $N = 934$.

project on PSU which addressed two different research questions and resulted in two different studies. A first study empirically tested the Pathways Model of problematic smartphone use and was published elsewhere [16]. The second study is the current one. No other studies are planned to be published with the current dataset. No overlapping results were presented in both studies, and the questionnaires used to assess smartphone use in both studies were not the same. Raw data and supplementary analyses can be obtained via the Open Science Framework (OSF) at https://osf.io/r5mdy/.

4.2. Measures

4.2.1. Smartphone impact scale (SIS)

The SIS [77] is a 26-item scale developed in Italian to comprehensively account for the different cognitive, affective, social and behavioral impacts of the smartphone in everyday life. Specifically, the SIS consisted of the following seven dimensions: (1) loss of control of smartphone use, which measures smartphone overuse and its interference in daily life (three items; α = 0.88; sample item: “Others tell me I spend too much time on the smartphone”); (2) nomophobia, which is the fear of being not able to use the smartphone (four items; α = 0.80; sample item: “If the smartphone is turned off, I feel lost”); (3) smartphone-mediated communication, which measures the preference for communicating via smartphone vs. face to face (four items; α = 0.85; sample item: “I prefer to talk about my feelings via smartphone than face to face”); (4) emotion regulation through smartphone usage, which is the use of the smartphone to cope with negative internal states (four items; α = 0.92; sample item: “When I feel pressured, using the smartphone makes me feel better”); (5) smartphone support for romantic relationships, which measures the role of the smartphone in maintaining a relationship with the partner (three items; α = 0.85; sample item: “The smartphone helped me (or helps me) keep my relationship alive”); (6) smartphone task support, which measures the usefulness of different functionalities of the smartphone in everyday life (four items; α = 0.69; sample item: “The smartphone helps me remember what I have to do”); and (7) awareness of smartphone negative impact, which measures awareness of negative effects deriving from excessive smartphone use (four items; α = 0.74; sample item: “The smartphone is an overwhelming device”). According to Pancani et al. [77], *loss of control of smartphone use*, *nomophobia*, *smartphone-mediated communication*, and *emotion regulation through smartphone usage* are the dimensions most related to PSU severity, especially the former two. The SIS dimensions were measured on a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The SIS is reliable and scores are strongly associated with a series of psychosocial constructs related to PSU severity and self-reported smartphone use and its primary functionalities [77].

4.2.2. Social interaction anxiety scale (SIAS)

The SIAS ([63]; Italian validation: [88]) is a 19-item scale developed to assess anxiety over social interactions (e.g., “I have difficulty talking with other people”). The SIAS dimension was measured on a 5-point Likert scale, ranging from 0 (*not at all*) to 4 (*extremely*). Cronbach’s alpha for the scale in the present study was 0.92. The SIAS, as well as the Italian version of the SIAS, showed robust psychometric properties [63,88] and convergence validity with other similar measures [83].

4.2.3. Depression, anxiety and stress scales – 21 (DASS – 21)

The DASS-21 ([42]; Italian validation: [11]) is a 21-item scale that evaluates stress (e.g., persistent state of overarousal and low frustration tolerance), depression (e.g., loss of self-esteem/incentives and depressed mood) and general anxiety (e.g., fear and anticipation of negative events). Items are rated on a 4-point scale ranging from 0 (*never or almost never*) to 3 (*almost always or always*). Cronbach’s alpha for depression, anxiety, and stress in the present study was 0.89, 0.84, and 0.86, respectively. The DASS-21 is reliable, and scores on the various subscales are correlated with other measures that assess depression and anxiety symptoms [42].

4.2.4. Short UPPS-P impulsive behavior scale (S-UPPS-P)

The S-UPPS-P ([8]; Italian validation: [25]) is a 20-item scale developed to assess impulsive behavior in five different impulsivity facets of negative urgency (tendency to act rashly under conditions of intense negative affect), lack of premeditation (tendency to fail to take into account the consequences of an act before engaging in that act), lack of perseverance (difficulties remaining focused on a task that may be long, boring, or difficult), sensation seeking (propensity to enjoy and pursue exciting activities and new experiences that may or may not have an element of danger) and positive urgency (tendency to act rashly under conditions of intense positive affect). Responses are rated on a 4-point Likert scale ranging from 1 (*strongly agree*) to 4 (*strongly disagree*). All scales demonstrated adequate internal consistency in the present sample: negative urgency (α = 0.82), premeditation (α = 0.82), perseverance (α = 0.90), sensation seeking (α = 0.87) and positive urgency (α = 0.79). Previous studies showed that the various components of the S-UPPS-P are reliable (e.g., high internal consistency and test-retest fidelity), and their validity was demonstrated through relationships with various psychopathological symptoms and problematic behaviors such as substance abuse [8,25].

4.2.5. Obsessive-compulsive inventory – revised (OCI-R)

The OCI-R ([36]; Italian validation: [61]) is an 18-item scale that evaluates six areas of obsessive-compulsive experiences, in line with epidemiological studies of the core obsessive-compulsive symptom dimensions, over the preceding month. Specifically, the six dimensions are washing (α = 0.79), checking/doubting (α = 0.69), obsessing (α = 0.88), mental neutralizing (α = 0.79), ordering (α = 0.85), and hoarding (α = 0.81). All items are scored on a Likert scale from 0 (*not at all*) to 4 (*extremely*). Previous studies showed that the various subscales of the OCI-R are reliable and moderately to strongly associated with other global measures of OCD and other psychopathological symptoms such as depression [36,61].

4.2.6. Rosenberg self-esteem scale (RSES)

The RSES ([84]; Italian version: [81]) is a 10-item scale that assesses positive and negative evaluations of oneself as a global trait of self-esteem. Items are rated on a 4-point scale from 1 (*strongly disagree*) to 4 (*strongly agree*). Cronbach’s alpha for the scale in the present study was α = 0.90. The Italian version of the RSES demonstrated adequate reliability and its validity was shown through relationships with depression, anxiety, perceived social support, life satisfaction, and masculinity [81].

4.3. Data analysis

Data analysis consisted of two successive steps. The first step aimed at identifying profiles of smartphone users through LPA, a statistical technique that allows the detection of groups of individuals (i.e., classes or profiles) that are homogeneous at the levels of a set of variables (for an overview, see [105]). Therefore, LPA was performed on the composite scores of the seven dimensions of the SIS [77] to compare solutions that extract different numbers of classes, using a maximum likelihood robust to non-normality (MLR) estimator. Before performing the LPA, we mean-centered the scores in the SIS dimensions to increase the interpretation of the profiles.

The optimal solution (i.e., the most adequate number of classes to represent our data) was determined based on both statistical and theoretical considerations. Statistically speaking, the guidelines on how to properly conduct an LPA suggest evaluating multiple indices simultaneously, also recommending that the interpretability and theoretical utility of the profiles be considered in order to choose the optimal solution [75,86,90,102]. Statistical considerations were based on the following indices as useful methods for comparing two models: (1) the Akaike information criterion (AIC), (2) the Bayesian information criterion (BIC), and (3) the sample-size adjusted BIC (SABIC), which are model fit indices; (4) the entropy of the solution, which indicates the extent to which classes are distinct from one another; (5) the classes' posterior probability, representing the accuracy by which individuals are assigned to a class; (6) the Lo-Mendell-Rubin (LMR); and (7) the bootstrapped likelihood ratio (BLRT) tests. Lower values of the AIC, BIC, and SABIC indicate a better fitting model [49,69]. Entropy and posterior probabilities range from 0 to 1 and higher values indicate better classification. The LMR and the BLRT test the −2* log-likelihood difference between two subsequent models extracting k and k–1 classes. Therefore, a significant *p*-value associated with these tests indicate that the larger solution (i.e., k classes) fits the data significantly better than the more parsimonious one (i.e., k–1 classes), and thus the former should be preferred [74]. Because the LMR and BLRT tests were run multiple times to compare different pairs of solutions, critical significance levels were computed by using the Benjamini-Hochberg method [5] to control the false discovery rate. Concerning fit indices, no decisive indications about which is the best performing index exist. However, the BLRT and the BIC were identified as the most accurate indices in several methodological papers [47,69,74,99].

Although the aforementioned indices could provide useful guidelines for model selection, theoretical considerations are fundamental in evaluating LPA solutions and selecting the optimal one, especially when no clear indications come from statistical indices [70,75,86,90,102,106]. A good solution must include interpretable and meaningful profiles in light of the literature. According to Spurk et al. [90], "if the additional profile adds a substantial new variable formation (e.g., a qualitatively new profile) to the prior solution, the new profile might be retained" (p. 13). Moreover, the number of classes extracted depends on the trade-off between accuracy and parsimony: estimating more classes means being more precise in the identification of profiles, but it also increases model complexity and might decrease the interpretability of the profiles. A rule of thumb recommends not estimating a profile if it includes <1.0% of the sample size or fewer than 25 individuals [59], whereas profiles representing at least 5.0% of the sample can be considered sufficiently large [75].

After the best LPA solution was determined, profiles of smartphone users were compared regarding sociodemographic variables (i.e., age and gender) and psychological variables commonly related to PSU severity, namely, impulsivity traits (negative urgency, positive urgency, lack of premeditation, lack of perseverance, and sensation seeking), self-esteem, and psychopathological symptoms (anxiety, depression, stress, social anxiety, and OCD symptoms). Specifically, we applied the three-step BCH method [3] to estimate distal outcome differences among profiles by minimizing classification inaccuracy deriving from the LPA. This technique is based on the chi-square distribution; hence, we estimated effect size by using Cramer's V.

These analyses were exploratory in nature and not preregistered. The statistical software Mplus, version 8 [72], was used for the analysis.

5. Results

5.1. Identification of profiles of smartphone impact

Descriptive statistics and correlations of the SIS dimensions are reported in Table 2. A total of five LPA solutions were tested and carefully evaluated to estimate two to six latent classes. Statistical indices are reported in Table 3. No more than six classes were estimated because the six-class solution (i.e., model K6) included a profile (i.e., $C6_{K6}$) that accounted for only 1.9% of the sample, and larger models could only increase the likelihood of finding small classes. Moreover, increasing model complexity to estimate such a poorly representative class contrasted with the principle of parsimony; hence, model K6 was excluded from the list of plausible solutions. On the other hand, the two-class solution (i.e., model K2) yielded the highest values of entropy and posterior probabilities, but it was excluded for two main reasons. First, all the other statistical indices suggested that estimating more classes was associated with a significantly better fit; and second, two classes were considered too few to account for the complexity of configurations that could emerge from the seven dimensions of the SIS.

The remaining models (i.e., three-, four-, and five-class solutions) showed good and comparable values of entropy and posterior probability, whereas the AIC, BIC, SABIC, BLRT, and LMR yielded mixed results. Indeed, all of these fit indices favored the five-class solution (i.e., model K5), whereas LMR supported the three-class solution (i.e., model K3). According to the literature [47,69,74,99], the BIC and the BLRT are more accurate than the LMR in determining the number of classes. However, a qualitative evaluation of the profiles is mandatory to adequately choose the optimal solution [70,75,86,90,102,106]. Thus, we evaluated and compared models K3, K4, and K5 from a theoretical point of view, considering the interpretability and meaningfulness of the profiles that emerged from each solution.

The classes estimated by model K3, graphically depicted in Fig. S1 (see supplemental materials at https://osf.io/r5mdy/), mainly differed quantitatively. Indeed, although some SIS dimensions showed similar levels across classes (e.g., *awareness of smartphone negative impact*), those that were more related to PSU severity (i.e., *loss of control of smartphone use*, *nomophobia*, *smartphone-mediated communication*, and *emotion regulation through smartphone usage*) showed large differences across classes. Specifically, $C1_{K3}$ was characterized by low levels in most SIS dimensions, showing comparable scores for those more related to PSU severity; $C2_{K3}$ was characterized by levels around the sample mean for all SIS dimensions; and $C3_{K3}$ was characterized by levels above the sample mean for most SIS dimensions, especially those that were more related to PSU, among these, *loss of control of smartphone use*. Thus, since differences were mainly quantitative, the profiles for $C1_{K3}$, $C2_{K3}$, and $C3_{K3}$ were classified as "users with low smartphone impact," "users with average smartphone impact," and "problematic smartphone users," respectively.

These three profiles were clearly distinguishable in the other two models as well. $C1_{K3}$ was almost identical to $C1_{K4}$ (see Fig. 1) and to $C1_{K5}$ (see Fig. S2 in the supplementary materials at https://osf.io/r5mdy/),

Table 2
Descriptive statistics and correlations of the SIS dimensions.

SIS Dimensions	*M* (*SD*)	LC	NP	SC	ER	SR	TS	AN
LC	1.81 (0.89)	1						
NP	2.62 (0.95)	0.44*	1					
SC	1.89 (0.91)	0.42*	0.34*	1				
ER	2.20 (1.00)	0.49*	0.46*	0.43*	1			
SR	2.41 (1.11)	0.23*	0.31*	0.32*	0.27*	1		
TS	3.18 (0.81)	0.14*	0.25*	0.13*	0.22*	0.28*	1	
AN	2.82 (0.83)	0.02	−0.11*	−0.01	−0.00	−0.02	−0.19*	1

Note. SIS = Smartphone Impact Scale; LC = loss of control of smartphone use; NP = nomophobia; SC = smartphone-mediated communication; ER = emotion regulation through smartphone usage; SR = smartphone support to romantic relationships; TS = smartphone task support; AN = awareness of smartphone negative impact.
* $p < .01$.

Table 3
Results of latent profile analysis: statistical indices of the solutions.

LPA solutions	nfp	AIC	BIC	SABIC	BH crit	2ΔLL	LMR *p*	BLRT *p*	Entropy	n (%)	PP
K2 (2 classes)	22	16,622.4	16,728.9	16,659.0	0.01	938.6	< 0.001	< 0.001	0.80		
$C1_{K2}$										638 (68.3)	0.96
$C2_{K2}$										296 (31.7)	0.91
K3 (3 classes)	30	16,380.0	16,525.2	16,430.0	0.02	258.4	< 0.001	< 0.001	0.73		
$C1_{K3}$										384 (41.1)	0.89
$C2_{K3}$										383 (41.0)	0.84
$C3_{K3}$										167 (17.9)	0.93
K4 (4 classes)	38	16,290.0	16,473.7	16,353.0	0.03	106.2	0.216	< 0.001	0.74		
$C1_{K4}$										343 (36.7)	0.87
$C2_{K4}$										362 (38.8)	0.81
$C3_{K4}$										147 (15.7)	0.90
$C4_{K4}$										82 (8.8)	0.83
K5 (5 classes)	46	16,174.3	16,396.9	16,250.8	0.04	124.4	0.279	< 0.001	0.74		
$C1_{K5}$										253 (27.1)	0.86
$C2_{K5}$										352 (37.7)	0.80
$C3_{K5}$										114 (12.2)	0.90
$C4_{K5}$										109 (11.7)	0.84
$C5_{K5}$										106 (11.3)	0.79
K6 (6 classes)	54	16,095.2	16,356.6	16,185.1	0.05	95.1	0.637	< 0.001	0.77		
$C1_{K6}$										256 (27.4)	0.86
$C2_{K6}$										341 (36.5)	0.80
$C3_{K6}$										101 (10.8)	0.83
$C4_{K6}$										107 (11.5)	0.82
$C5_{K6}$										111 (11.9)	0.89
$C6_{K6}$										18 (1.9)	0.92

Note. nfp = number of free parameters; AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = Sample size adjusted BIC; BH crit = Benjamini-Hochberg critical value; 2ΔLL = 2 times log-likelihood difference; LMR *p* = *p*-value associated with the Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT *p* = *p*-value associated with the bootstrapped likelihood ratio test; n (%) = number and percentage of class members; PP = posterior probability of a class.

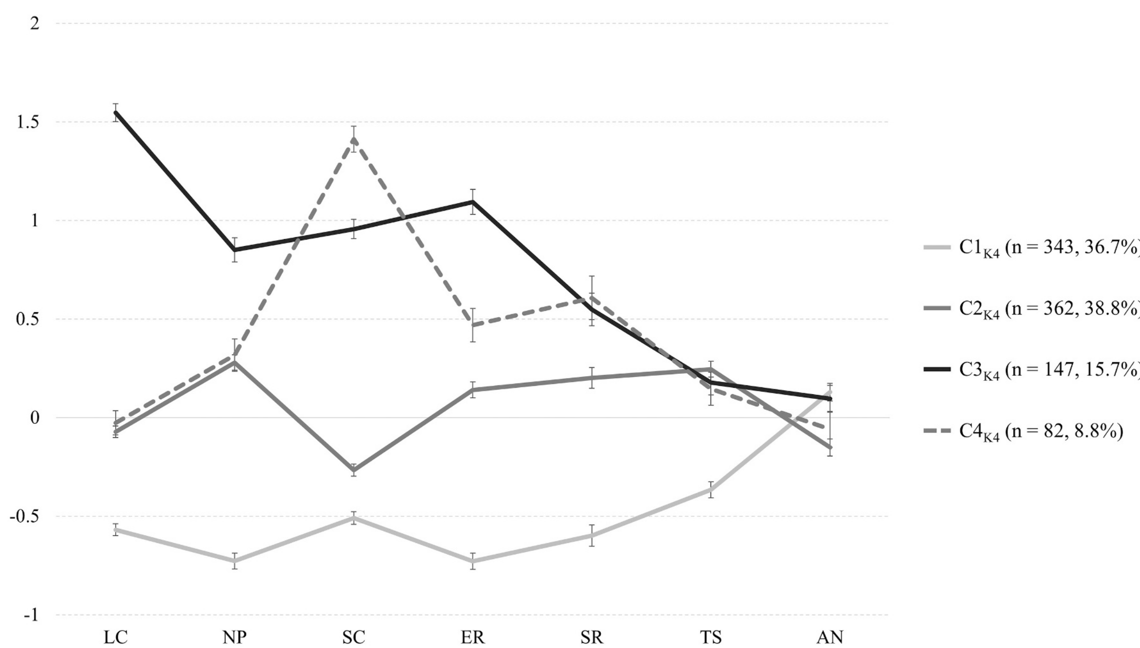

Fig. 1. The four-class solution (Model K4): scores are centered on sample mean.
Note. LC = loss of control of smartphone use; NP = nomophobia; SC = smartphone-mediated communication; ER = emotion regulation through smartphone usage; SR = smartphone support of romantic relationships; TS = smartphone task support; AN = awareness of negative smartphone impact.

although the latter showed a slightly higher score for *smartphone task support*. Similarly, the silhouette for $C3_{K3}$ was recognized in $C3_{K4}$ and $C3_{K5}$, although $C3_{K5}$ showed a slightly higher score for *smartphone-mediated communication*. The most visible changes were observed for the configuration of $C2_{K3}$, which seemed to increasingly approach the mean as the number of estimated classes increased. The major difference between $C3_{K3}$ and $C3_{K4}$ was observed for *smartphone-mediated communication*, which went from slightly above to slightly below the sample mean; a similar decrease was observed when $C3_{K4}$ and $C3_{K5}$ were compared for the remaining SIS dimensions that were more related to PSU. However, these differences were not considered large enough to change the interpretation (and name) of the profiles that emerged across the three models and, thus, were not crucial for the choice of optimal model.

A brand new profile appeared in model K4 (see Fig. 1) that was clearly different from the three earlier mentioned profiles and that was also observed (again, with some slight differences) in model K5. Indeed, $C4_{K4}$ and $C4_{K5}$ were characterized by medium-high levels for most of the

SIS dimensions (except for *smartphone task support* and *awareness of smartphone negative impact*, which were close to the sample means) and an exceptionally high level for *smartphone-mediated communication*. This feature was considered crucial for both the interpretation of the profile, which was accordingly named "users favoring online interactions," and an appropriate and complete description of the possible configurations that could emerge from the SIS. For the latter reason, model K3 was excluded from the list of plausible optimal solutions because it did not include any profile similar to $C4_{K4}$ or $C4_{K5}$.

Conversely, the new profile that emerged in model K5 (i.e., $C5_{K5}$) was not considered as crucial (and necessary) as the *users favoring online interactions* profile. Indeed, the configuration of $C5_{K5}$ was a mix of other classes: very close to the *users with average smartphone impact* profile for the majority of the SIS dimensions, almost identical to the *users favoring online interactions* profile for *nomophobia* and *emotion regulation through smartphone usage*, and characterized by an exceptionally high score in *loss of control of smartphone use*, comparable with what was observed for the *problematic smartphone user* profile. These different attributes did not allow us to identify a proper name for this profile. Moreover, among all classes estimated over all models performed, $C5_{K5}$ was the most unstable, showing the lowest posterior probability. For these reasons, model K5 was also excluded, and the four-class model (i.e., K4) was retained as the optimal solution to explain our data (graphically depicted in Fig. 1).

5.2. Differences among classes

The four profiles that emerged in model K4 (i.e., "users with low smartphone impact," "users with average smartphone impact," "problematic smartphone users," and "users favoring online interactions") were compared by using the BCH method. Concerning sociodemographic characteristics, age did not differ among profiles, $\chi^2(3) = 1.52$, $p = .68$, $V = 0.023$. Conversely, profiles showed different gender distributions, $\chi^2(3) = 45.74$, $p < .001$, $V = 0.128$. Specifically, males were overrepresented in the *problematic smartphone users* profile ($C3_{K4}$).

Concerning psychological variables, the results of the BCH method are reported in Table 4 and graphically depicted in Fig. 2. All the comparisons yielded significant results, indicating that the four profiles differed at the level of the psychological variables considered; the only exception was sensation seeking, which showed similar levels for all profiles. Specifically, we found a pattern that characterized most of the psychological variables. The scores observed for the *users with low smartphone impact* profile ($C1_{K4}$) were significantly lower than those for the *users with average smartphone impact* profile ($C2_{K4}$), which, in turn, showed significantly lower scores than for those observed for the *problematic smartphone users* profile ($C3_{K4}$). This pattern emerged for the three variables that measured emotional symptoms (i.e., depression, anxiety, and stress), social anxiety, negative and positive urgency, and every type of obsessive-compulsive symptoms. The same pattern was also observed for self-esteem, although the order of the three latent classes was the opposite, with the *users with low smartphone impact* profile showing the highest score, followed by *users with average smartphone impact* and *problematic smartphone users*. A different pattern was observed only for lack of premeditation and lack of perseverance impulsivity traits, for which users with a low and average smartphone impact (i.e., $C1_{K4}$ and $C2_{K4}$) showed an almost identical level, which was significantly lower than that of *problematic smartphone users* ($C3_{K4}$).

Conversely, the level of psychological variables for the *users favoring online interactions* profile ($C4_{K4}$), compared with that observed for the other profiles, suggested a more complex configuration. Indeed, the *users favoring online interactions* showed the following: (1) the highest level of social anxiety and the lowest level of self-esteem, comparable to (and not significantly different from) those observed for the *problematic smartphone users* profile; (2) a medium-high level of depression, negative urgency, positive urgency, and ordering, which were between those observed for the *problematic smartphone users* and the *users with average smartphone impact* profiles, but not significantly different from them; (3) an average level of anxiety, stress, checking/doubting, obsessing, mental neutralizing, and hoarding, comparable to those observed for the *users with average smartphone impact* profile; (4) an average level of lack of perseverance, which was significantly different from that observed for all other profiles; (5) a low-medium level of washing, between those observed for the users with low and average smartphone impact, but not significantly different from them; and (6) a low level of lack of premeditation, comparable with that of the users with low and average smartphone impact.

Table 4
Comparison of the profiles on personality and psychopathology variables.

Variable	df	χ^2	p	Cramer's V
Psychological distress				
Depression	3	76.26	< 0.001	0.165
Anxiety	3	78.67	< 0.001	0.168
Stress	3	58.48	< 0.001	0.144
Social anxiety	3	163.95	< 0.001	0.242
Self-esteem	3	63.17	< 0.001	0.150
Impulsivity				
Negative urgency	3	70.06	< 0.001	0.158
Positive urgency	3	45.88	< 0.001	0.128
Lack of premeditation	3	17.50	0.001	0.079
Lack of perseverance	3	49.32	< 0.001	0.133
Sensation seeking	3	2.99	0.393	0.033
Obsessive-compulsive disorder				
Washing	3	69.00	< 0.001	0.157
Checking/Doubting	3	72.87	< 0.001	0.161
Obsessing	3	92.90	< 0.001	0.182
Mental neutralizing	3	81.32	< 0.001	0.170
Ordering	3	48.99	<0.001	0.132
Hoarding	3	69.07	< 0.001	0.157

6. Discussion

The current study aimed to disentangle the heterogeneity of the impacts of the smartphone by identifying subtypes of smartphone users based on a person-centered analytical approach, as well as to compare these subtypes in terms of PSU-relevant personality traits and psychopathological symptoms. Our study identified four different subgroups of smartphone users: (i) *users with low smartphone impact* presented with low scores in most SIS dimensions; (ii) *users with average smartphone impact* presented with medium scores for all SIS dimensions; (iii) *problematic smartphone users* presented with elevated SIS dimensions, in particular regarding the loss of control, nomophobia, and emotion regulation dimensions; and (iv) *users favoring online interactions*, who especially presented with an elevated level of smartphone-mediated communication. In line with our hypothesis, users with *low* and *average smartphone impact* in general have low impulsivity and psychopathological symptoms, and *problematic users* presented with more marked impulsivity traits, psychopathological symptoms, and lower self-esteem.

The *problematic smartphone user* profile is composed of users who are characterized by high scores on loss of control, nomophobia, and emotion regulation dimensions. This profile displays some characteristics (e.g., tolerance and withdrawal-like symptoms) already found in the so-called classes of high-risk/more severe smartphone users in previous studies [30,31,110]. Yet, our study showed that this profile is also characterized by specific features (e.g., marked smartphone-mediated communication and emotion regulation through smartphone usage) not documented (or assessed) in previous research. *Problematic smartphone users* are characterized by higher levels of psychopathological symptoms (i.e., depression, anxiety, stress, and OCD symptoms) and high impulsivity traits (except for sensation seeking). This class appears to be in line with the I-PACE model introduced by Brand et al. [12,13], which posits that predisposing variables, including temperamental features alongside with psychopathology and maladaptive coping styles, constitute vulnerability factors for developing PSU symptoms. As

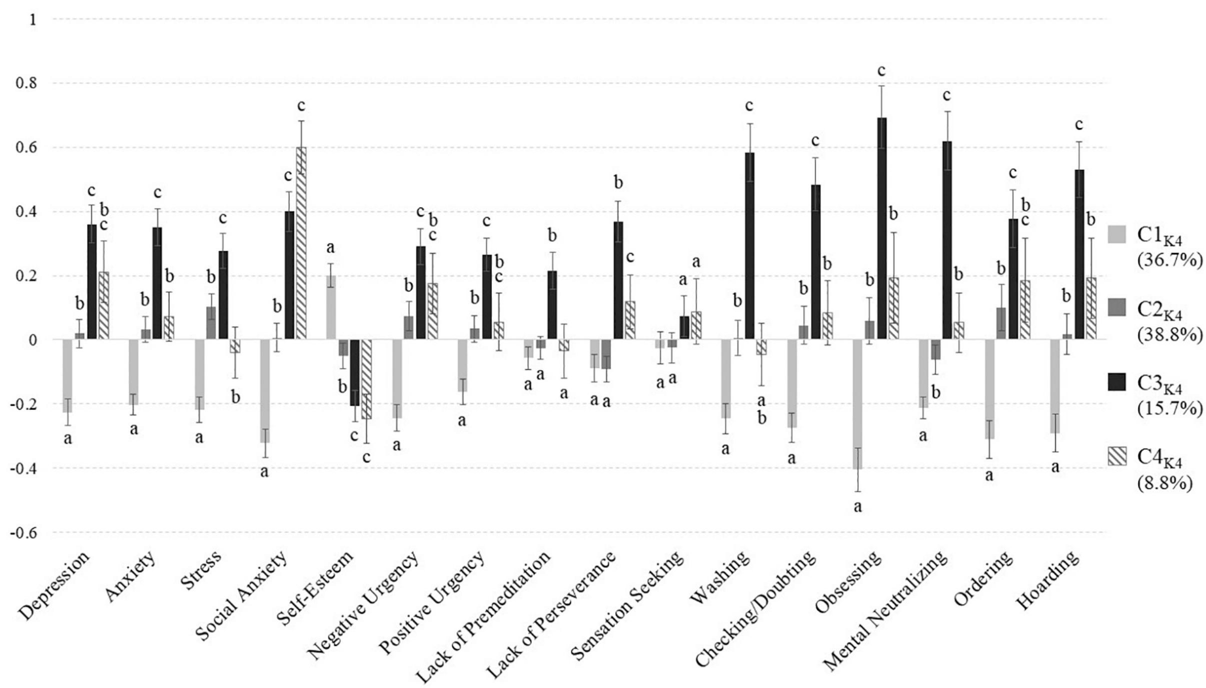

Fig. 2. The results of the ANOVAs for personality and psychopathology: scores are centered on sample mean.
Note. Same letters indicate that means are not significantly different.

suggested in previous studies (e.g., [82,109]), the high accessibility and availability of smartphones may promote loss of control among vulnerable users who use them as a way to regulate affect. It is likely that this subgroup of smartphone users lacks access to adaptive emotion regulation strategies [44]. *Problematic smartphone users*, who frequently lose control over smartphone use, are also characterized by a specific impulsivity profile. They display heightened negative urgency (i.e., the tendency to act rashly while faced with intense negative emotional contexts) and positive urgency (i.e., the tendency to act rashly in intense positive emotional contexts). Both negative and positive urgency have been found to be robust predictors of various problematic behaviors displayed to regulate mood in the short term [2,24], including problematic mobile phone use [7,100]. Thus, it is likely that individuals included in the *problematic smartphone users* class are more prone to overuse the smartphone to regulate emotional states [22,29]. On the other hand, they report an elevated lack of premeditation (i.e., the tendency to act without adequate consideration of potential outcomes or planning). Individuals characterized by low premeditation present an inability to carefully think before acting and poor decision-making skills [103,111], which has been linked to the tendency to use smartphones without considering the potential adverse consequences [6]. Lastly, *problematic smartphone users* show a higher lack of perseverance, which indexes a reduced capacity to resist distracting stimuli, tolerate boredom and complete tasks [103]. Lack of perseverance was linked to PSU severity in previous studies [6,7], and boredom proneness (i.e., the trait-based tendency to experience boredom) is a known risk factor for PSU [28,113]. It is thus likely that *problematic smartphone users* frequently attempt to relieve the aversive state of boredom by (over)using their smartphone to obtain positive reinforcement in an easily accessible way [28,101]. Boredom proneness is also characterized by intrusive and ruminative thoughts, and it can be hypothesized that using the smartphone might help to get rid of such thoughts [8,108].

The fact that *problematic smartphone users* have high levels of OCD symptoms is in line with previous studies that showed an association between addictive use of technology or the Internet and obsessive-compulsive symptoms (e.g., [1,67]). Unexpectedly, regarding specific OCD symptoms, we found that obsessive thinking, rather than checking and/or hoarding proneness, was the main OCD feature characterizing problematic smartphone users. This result has also been reported in previous studies that described obsessive thoughts as important feature of Internet use disorders (e.g., [26,68]). It can thus be hypothesized that for these users, excessive smartphone use might constitute a ritual-like behavior that relieves the anxiety induced by maladaptive obsessive thoughts [55]. Overall, similar to what was previously argued in the context of problematic use of the Internet, our results seem to suggest PSU proneness to be characterized by a pattern of symptoms resulting from a disturbance of mechanisms underlying both affective symptoms and symptoms from the obsessive-compulsive spectrum. Among such mechanisms, functional alterations in the reward network have been related to addictive behaviors, depression, and OCD [78]. Moreover, abnormalities in reward processing, inhibition, and impulse control have been also highlighted in technology-related problematic behaviors (e.g., [12]). It is also worth noting that problematic users displayed a high level of hoarding, which is in line with the proposal that “digital hoarding” may be a form of hoarding disorder, considered as the accumulation of digital information to the point of loss of perspective that may lead to stress symptoms [97]. It is possible that, among problematic smartphone users, hoarding is manifested as an over-accumulation of digital objects (e.g., photos, emails, files), and excessive attachment and distress in anticipation of such objects being discarded [60]. Interestingly, the profile of OCD symptoms shown in this class of smartphone users partially matches that of obsessive-compulsive-prone individuals, who are also characterized by heightened urgency and a lack of perseverance [112]. In relation to the current debates about the conceptualization of addictive smartphone use, it is worth noting that the characteristics of this profile of problematic smartphone users could reflect weak impulse control and obsessive-compulsive features [21,37,57]. Further research is thus required to establish such relationships.

We identified a specific class of *users who favored online interactions,* which clearly differentiates them from the other profiles identified in the present study (*users with low/average smartphone impact* and *problematic smartphone users*) and from the results of previous research [30,31,110]. This profile is composed of users who are characterized by a marked preference for smartphone-mediated communication and who exhibit a high level of social anxiety symptoms and a low level of self-esteem. The characteristics of this profile appear to be well in line with the compensatory internet use theory [48], which considers lower self-esteem and high social anxiety as important risk factors for individuals to develop problematic patterns of technology usage. For instance, such individuals tend to send a considerable number of messages (e.g., for reassurance seeking) or may excessively rely on their smartphones to minimize the discomfort they feel in social situations [54]. *Users favoring online interactions* may have a higher preference for online social interactions, which refers to the beliefs about being safer and more confident with online communication than with face-to-face interactions [18]. From this perspective, it could be the case that *users favoring online interactions* are socially anxious people with poor self-esteem who experience difficulties in offline social interactions [41,87]. They would prefer a smartphone-based app to communicate (e.g., talking about feelings/worries online), thus avoiding the threat of face-to-face interactions and perceiving themselves as more efficacious and confident. Therefore, smartphone users who constantly favor online interactions over face-to-face interactions might develop difficulties in regulating smartphone use, thus experiencing an escalation of symptoms that is comparable, but does not completely overlap with, that of problematic smartphone users [62]. These users may excessively use their smartphones for communication in an attempt to cope with adverse emotional states and unmet needs or a way to promote or maintain pleasant emotions, for instance, by using specific smartphone apps [92] or by connecting on social networking sites to seek social support [58]. Overall, this class might be considered as a vulnerable group of smartphone users characterized by maladaptive online behaviors and more psychological difficulties compared with *users with low and average smartphone impact*. From a clinical point of view, it could be useful to identify and modify, in these users, the specific dysfunctional beliefs about the safety of online interactions that promote and perpetuate social anxiety and negative self-esteem.

Two other classes (representing about 75% of the sample) were identified, who globally correspond to individuals who have no or few interference effects resulting from smartphone use. These classes – *users with low smartphone impact* and *users with average smartphone impact* – are characterized by low-medium scores on the dimensions that have been related to PSU severity in past research (e.g., loss of control of smartphone use, nomophobia, smartphone-mediated communication, and emotion regulation through smartphone usage). They also reported low-medium psychopathological symptoms and impulsivity traits and a high level of self-esteem. This suggests that, for them, the smartphone does not serve to manage their psychological distress or to help them face potential discomfort in offline social situations. They also have low impulsivity, meaning that they are more able to regulate their smartphone use and are less affected by distractibility or urges to use their smartphone.

6.1. Limitations

Some limitations of the study methodology should be pointed out. First, the cross-sectional design allowed us to examine only the current impacts of smartphone use and the psychological variables of users, and their causal associations could not be confirmed. For example, *the problematic smartphone user profile* was characterized by higher levels of depression, anxiety, and stress. Notably, as some authors have reported (e.g., [80]), it is also possible that a vicious cycle between psychopathology and PSU symptoms may develop, whereby higher levels of emotional distress lead to more problematic usage, which, in turn, may increase negative emotions. However, given that the majority of available studies are cross-sectional, the direction of the association between psychopathological and PSU symptoms remains unclear, thus requiring further investigation [15]. Second, since data were collected via self-report measures, further studies that take other measurement approaches should be conducted to complement our approach. For example, smartphone use can be measured with more specific instruments (e.g., using smartphone apps that allow to collect objective trace data; [85]), personality dimensions can be measured by using ecological momentary assessment [94] and virtual reality to study human social interaction. Third, the current study selected only a specific demographic group (i.e., young adults, a large majority of whom were undergraduate students with regular access to the Internet, predominantly females, and unknown living accommodations), thus limiting the generalizability of our findings. Fourth, despite the link to the questionnaire being published on social media groups of the University of Padova (e.g., study groups, class groups, faculty groups, groups for sharing online survey, lab groups etc., which are all dedicated to college students) and the informed consent explicitly stating that the study was focused on college students, information about actual college student status and living accommodations was not collected, implying that we cannot exclude the possibility that our sample comprises some participants who are not college students or who do not live in the area of University of Padova. Fifth, the fit indices did not provide clear directions regarding the optimal number of classes to choose, making it impossible to state which model was superior from a statistical standpoint. According to current guidelines in LPA research, it is thus crucial to determine the number of classes to retain in terms of their interpretability and theoretical value [75,86,90,102]. Finally, only bivariate comparisons were performed between the latent profiles, thus it is possible that some differences identified between the profiles are explained by variables non considered in the study.

7. Conclusions

In the present study, we identified four distinct classes of smartphone users based on the impact that this device have on their daily lives. Most participants were classified into two groups of users (representing 75% of the sample) having a low-average impact of smartphones on their daily lives, which further supports the need to avoid overpathologizing smartphone use [10,66]. At the theoretical level, the present study emphasizes that the impact of smartphones on everyday life is highly heterogeneous and it depends on a wide range of psychological factors in accordance with the pathways model of problematic mobile phone use [9,16], which considers multiple forms and etiologies of PSU (e.g., excessive reassurance and impulsive pathways). At the clinical level, the heterogeneity found in the present study calls for the development of personalized (custom-made) interventions that target specific psychological mechanisms (e.g., [17,79]).

Data availability statement

Raw data and supplementary analyses can be obtained via the Open Science Framework (OSF) at https://osf.io/r5mdy/.

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Supplementary data

Figure S1 and Figure S2 are available on the Open Science Framework (OSF) at https://osf.io/r5mdy/.

Figure S1. The three-class solution (Model K3): scores are centered on sample mean.

Figure S2. The five-class solution (Model K5): scores are centered on sample mean.

Declaration of Competing Interest

None.

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