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Rumination and negative smartphone use expectancies are associated with greater levels of problematic smartphone use: A latent class analysis

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ABSTRACT

Problematic smartphone use (PSU) is related to psychopathology symptoms, such as depression and anxiety. However, less is known about how responses to and coping with psychopathology correlate with PSU. We conducted a web survey of 286 American college students, querying depression and anxiety symptoms, rumination (a coping process to avoid negative emotion), PSU, and expectancies about smartphone use for mood alleviation. We conducted latent class analysis (LCA) of PSU symptom ratings, finding support for two latent subgroups of participants, involving mild and severe PSU, especially distinguished by severity of withdrawal symptoms. Rumination and negative smartphone use expectancies (i.e., to reduce distress) positively related to the more symptomatic PSU class. Results are discussed in context of the I-PACE theoretical model of problematic internet use (PIU). We emphasize the importance of response variables in I-PACE, such as internet-related cognitive bias and coping, over background psychopathology variables in influencing PIU and PSU.

1. Introduction

Excessive use of a smartphone has demonstrated adverse functional effects. Prior work has supported background psychopathology variables, such as depressive and anxious symptoms, that may influence smartphone overuse (reviewed in Thomée, 2018; Elhai et al., 2019a). Yet, little is known about how responses to and coping with psychopathology symptoms influences such overuse, including dysfunctional coping processes and internet-related cognitive biases. We examined psychopathology symptoms, dysfunctional coping, and smartphone use expectancy biases in relation to excessive smartphone use. We analyzed smartphone use with mixture modeling, empirically categorizing participants into groups based on use severity.

Excessive smartphone use is often labeled as "problematic smartphone use" (PSU) in the scientific literature. PSU comprises not only extreme use levels or use frequency of one's smartphone features (e.g., messaging, entertainment apps, etc.), but also associated symptoms seen in substance use disorders (e.g., withdrawal, tolerance, social impairment) (Chen et al., 2016; De-Sola Gutierrez et al., 2016; Montag et al., 2016; Lee et al., 2019). Thus PSU is not only defined by excessive frequency of use, but also associated functional impairment in daily life. Recent work by Montag et al., in press suggests that within the broad Internet Use Disorder (IUD)/problematic internet use (PIU) literature (i.e., not only involving smartphone) (reviewed in Kuss et al., 2014), PSU may be conceptualized as a more specific, "mobile form" of general IUD/PIU. This distinction is relevant because unlike the internet more generally (i.e., one one's computer), the smartphone's small size and portability enables persons to *constantly* access online (and offline) content, potentially causing overuse (with constant availability as a risk factor) (Elhai et al., 2017a).

We should clarify that PSU is alternatively referred to in scientific literature with synonymous, interchangeable terms, including "excessive smartphone use," "smartphone use disorder," and "smartphone addiction" (Thomée, 2018; Montag, 2019). We also provide the caveat that PSU is not a recognized clinical disorder (Panova and Carbonell, 2018). And it is important to be careful about placing PSU into the same class of addictions as drug or alcohol use disorders, even if similarities are observed with PSU (Billieux et al., 2015; Ryding and Kaye, 2018). Nonetheless, PSU could have similar brain chemical effects seen in drug addiction (Montag et al., 2016; Montag, 2019).

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Furthermore, PSU has dangerous health consequences, including pedestrian and motor vehicle accidents from concurrent use (Cazzulino et al., 2014; Kita and Luria, 2018), musculoskeletal pain in the hands and neck from overuse (Xie et al., 2016; Yang et al., 2019), and sleep impairment (Yang et al., press).

A body of research has examined influences of PIU and PSU severity that involve background, predispositional psychological and psychopathological variables (Brand et al., 2016, 2019). Personality variables linked with PSU include neuroticism and impulsivity (reviewed in Carvalho et al., 2018; recent evidence in Lachmann et al., 2019; Peterka-Bonetta et al., 2019). Psychopathology variables most consistently related to increased PSU are anxiety and depression severity (reviewed in Thomée, 2018; Elhai et al., 2019a). In fact, PSU's effect sizes are medium for depression and small to medium for anxiety (Elhai et al., 2019a). In the present paper, we included depression and anxiety severity as predisposing psychopathology symptom covariates of PSU severity. However, more recent conceptualizations and empirical studies have focused on additional contributing psychological influences of PSU, involving consequences from and coping with predisposing variables. Such consequences include dysfunctional coping and mood regulation, and internet-related cognitive bias, often exacerbating predisposing psychopathology's influence on PIU/PSU severity (Brand et al., 2016, 2019). Therefore, we also included covariates involving dysfunctional consequences from predispositional variables: rumination and expectancies about smartphone use, discussed next.

Dysfunctional emotional and cognitive coping processes have recently been linked with PSU severity. In particular, PSU severity demonstrates relationships with repetitive negative thinking, boredom proneness, dysregulated emotion, and fear of missing out on rewarding experiences or FOMO (reviewed in Elhai et al., 2019c). In the present work, we focus on rumination, a primary type of repetitive negative thinking, involving frequent negative thoughts about oneself (Samtani and Moulds, 2017). Rumination is theorized as a dysfunctional cognitive coping strategy for avoiding negative emotion (Nolen-Hoeksema et al., 2008), often accompanying depressive and anxious disorders (Aldao et al., 2010). As such, rumination would be considered a consequence from psychopathology, and maladaptive coping process, that can contribute to PIU and PSU severity (Brand et al., 2016, 2019). Several studies (albeit using correlational, single-sample designs) have discovered rumination related to increased PSU severity (Liu et al., 2017; Elhai et al., 2018b, 2020; Liu et al., press). Rumination is thought to influence PSU severity in that ruminating about personal and intimate relationships can drive people to excessively check and interact with their smartphone's messaging and social media apps for interpersonal-related notifications and content (Billieux et al., 2015; Elhai et al., 2019c). Such excessive interaction with interpersonal-related smartphone content can represent a form of excessive reassurance seeking behavior, aimed at reducing distress from increased rumination and depression symptoms (Billieux et al., 2015; Elhai et al., 2019c).

Additionally, internet-related cognitive biases are considered a consequence from psychopathology that can contribute to PIU/PSU (Brand et al., 2016, 2019). In particular, expectancies and false beliefs about effects of internet use are linked with PIU (Brand et al., 2016). Internet use expectancies may be positive (e.g., to feel better emotionally) or negative (e.g., to avoid distress) and are reinforcing if associated with desired effects of such use (Brand et al., 2016). Further, such reinforcement can lead to PSU (Chen et al., 2019). Studies demonstrate that both positive and negative use expectancies bivariately correlate with PIU severity (Brand et al., 2014; Wegmann et al., 2015; Wegmann and Brand, 2016, 2017). However, *smartphone* use expectancies have not been investigated.

We used latent class analysis (LCA) of continuous-scaled data (also known as latent profile analysis) to model PSU severity ratings. LCA is a type of mixture model (McLachlan et al., 2019) involving person-centered rather than variable-centered analysis. Thus, rather than testing correlations among variables, LCA examines similarities/differences among individuals and how such heterogeneity relates to other variables/covariates. Thus LCA can model population heterogeneity in a way in which correlational studies cannot, as such correlational studies assume that the sample is homogeneous and unitary. Consequently, LCA can provide an alternative, complementary perspective to correlational analyses of a research question. We discovered three relevant LCA studies, all conducted in one country (Korea), simultaneously examining PIU and PSU using summed scores rather than item-level data (Mok et al., 2014; Kim et al., 2016; Lee et al., 2018). One recent U.S. study used LCA with PSU ratings, finding three latent classes (Elhai et al., 2019b). Also relevant, Elhai and Contractor (2018) examined smartphone use frequency items (though not PSU) in U.S. participants, finding two classes.

1.1. Aims

Our overarching research questions were: how heterogeneous are our research participants with regard to PSU item severity, and to what extent do psychopathology symptoms and consequences from psychopathology correlate with such heterogeneity (i.e., latent class membership)? Specifically, our primary aim was to investigate PSU rating heterogeneity using LCA, exploring relationships with three types of covariates: a) depressive and anxious symptoms, as predisposing psychopathology variables, b) rumination, a dysfunctional coping process, and consequence from psychopathology, and c) smartphone use expectancies (positive and negative), a cognitive bias-related consequence from psychopathology relevant to PIU/PSU.

Thus we included background psychopathology variables, as well as consequences from psychopathology that can impact PSU severity, based on prior theory (Brand et al., 2016, 2019). We also covaried for sex, as some studies suggest women disproportionately engage in PSU (e.g., De-Sola Gutierrez et al., 2016). This sex difference may be the result of women using social features of their smartphones at greater levels than men do (van Deursen et al., 2015; Elhai et al., 2017b), given a greater social orientation experienced among women (Kawachi and Berkman, 2001). The value of this analysis is to augment the limited research base on heterogeneity of PSU symptoms (using LCA), and assess the influence of lesser, more recently studied covariates of PSU involving responses to psychopathology: dysfunctional ruminative coping, and internet-related cognitive bias.

1.2. Theory

We placed our research model in context of the Interaction of Person-Affect-Cognition-Execution (I-PACE) model of PIU (Brand et al., 2016, 2019). I-PACE assumes several categories of variables influencing PIU/PSU. First, underlying, predisposing characteristics are important, such as personality, mental health, genetics, and biology in general. Anxiety and depression are included in this category. Second, cognitive and affective consequences are important influences, such as coping styles, executive impairment, mood dysregulation, and internet-related cognitive bias. I-PACE assumes that this latter category involves responses to predisposing characteristics and can lead to healthy enjoyment through technology or excessive use. Rumination represents dysfunctional coping, and smartphone use expectancies represent cognitive bias, in this latter category of responses to psychopathology.

1.3. Hypotheses

H1) *Between 2–4 latent classes of participants should be revealed from PSU item ratings.* Two previous studies each discovered three latent classes, one based on PSU items (Elhai et al., 2019b) and the other one on PSU/PIU summed scores (Mok et al., 2014). Another study found four classes from PSU/PIU scores (Lee et al., 2018). Also relevant, Elhai and Contractor (2018) found two classes based on smartphone use frequency.

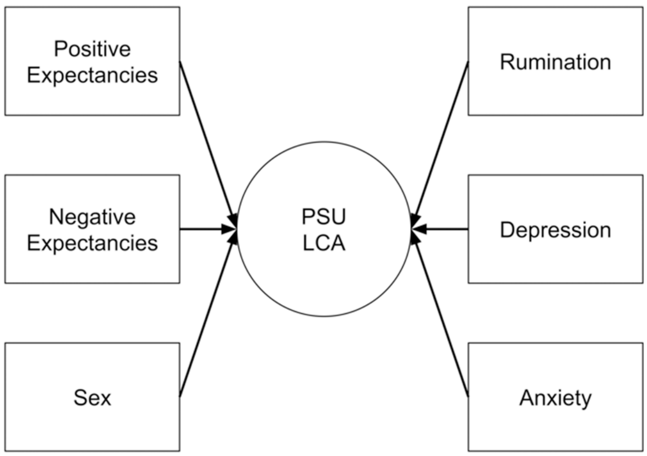

Fig. 1. Hypothesized model.
Note. PSU = Problematic smartphone use; LCA = Latent class analysis. The circle represents a latent class variable, while rectangles indicate observed variables.

H2) *Rumination should be positively related to more severe PSU latent class membership*. Rumination represents dysfunctional coping in I-PACE, influencing PIU/PSU (Brand et al., 2019). This hypothesis is supported by recent work finding rumination-PSU severity associations (Liu et al., 2017; Elhai et al., 2018b, 2020; Liu et al., press).

H3) *Anxiety and depression symptom severity should be positively related to more severe PSU latent class membership*. Anxiety and depression are predispositional variables in I-PACE, influencing PIU/PSU. This hypothesis is supported across the literature finding significant relationships between PSU and depression/anxiety severity (Thomée, 2018; Elhai et al., 2019a).

H4) *Smartphone use expectancies should be positively related to more severe PSU latent class membership*. Expectancies about internet use represent cognitive bias in I-PACE. Such expectancies - both positive and negative - demonstrate relations with PIU (Brand et al., 2014; Wegmann et al., 2015; Wegmann and Brand, 2016, 2017) and should extend to PSU, albeit only previously examined on a bivariate basis.

1.4. Research model

Our research model (Fig. 1) includes PSU items modeled with LCA. Covariates include depression, and anxiety symptoms as predisposing psychopathology variables within the I-PACE model, as well as rumination and positive and negative smartphone use expectancies as consequences from predisposing psychopathology in I-PACE (Brand et al., 2016, 2019). We also incorporated sex as a covariate of PSU (De-Sola Gutierrez et al., 2016), for above mentioned reasons.

2. Method

2.1. Participants and procedure

We recruited undergraduate smartphone users (age 18–25) from the introductory psychology course research pool of a large, Midwestern American university. In fall 2019, students enrolled through the department's online research portal, linked to an online consent statement, and if consenting, to a web survey. We followed procedures in compliance with the Declaration of Helsinki, and the university's IRB approved the study.

Of 313 apparent enrollees, we removed 16 duplicate attempts and 6 individuals who did not advance past initial demographic questions. We also excluded 5 participants responding with insufficient effort, having at least one uninterrupted string of many (20+) consecutive identical responses. The remaining 286 participants averaged 19.72 years old (SD = 2.60). Most were women (n = 180, 62.9%); freshman (n = 139, 48.6%) and sophomores (n = 92, 32.2%) were overrepresented. A majority were Caucasian (n = 223, 78.0%), with (non-mutually exclusive) representation from African Americans (n = 39, 13.6%), Asians (n = 21, 7.3%), and Latinx participants (n = 21, 7.3%).

2.2. Instruments

In addition to demographics, we administered the following instruments. Internal consistency estimates are indicated in Table 1.

2.2.1. Depression Anxiety Stress Scale-21 (DASS-21)

The DASS-21 has 21 items rated over the past week (Lovibond and Lovibond, 1995). Items are rated from 0 (“Did not apply to me at all”) to 3 (“Applied to me very much or most of the time”). We used the subscales for anxiety and depression (7 items each), with established reliability and validity (Scholten et al., 2017).

2.2.2. Ruminative Thought Style Questionnaire (RTSQ)

The RTSQ is a 20-item scale of current ruminative thought (e.g., “I can't stop thinking about some things”) (Brinker and Dozois, 2009). The measure is rated from 1 (“Does not describe me at all”) to 7 (“Describes me very well”). The scale has established psychometric properties (Claycomb et al., 2015).

2.2.3. Smartphone Addiction Scale-Short Version (SAS-SV)

The SAS-SV has 10 items, measuring current PSU severity (e.g., “I miss planned work due to smartphone use”) (Kwon et al., 2013). Items are rated from 1 (“Strongly disagree”) to 6 (“Strongly agree”). We slightly reworded items by providing a consistent first-person perspective (Duke and Montag, 2017). The scale is reliable and valid (Luk et al., 2018).

2.2.4. Smartphone Use Expectancies Scale

Brand et al. (2014) developed an 8-item Internet Use Expectancies Scale. Items are rated from 1 (“Completely disagree”) to 6 (“Completely agree”). The scale has subscales for positive (e.g., “experience pleasure”) and negative (e.g., “avoid loneliness”) expectancies, with adequate psychometrics (Brand et al., 2014). We modified the scale by inquiring about “my smartphone” instead of “the internet.”

Table 1
Internal consistency, means, and standard deviations for the primary variables, and differences across sexes.

Variable	Alpha	Sample M	Sample SD	Men M	Men SD	Women M	Women SD	F(1,284)	p	η_p^2
1. PSU	.86	27.88	9.41	25.74	7.61	29.14	10.14	8.97	.003	.03
2. Positive Smartphone Use Expectancies	.80	16.79	4.05	16.43	4.05	17.00	4.04	1.31	.25	.01
3. Negative Smartphone Use Expectancies	.79	15.18	4.80	13.76	4.56	16.02	4.76	15.41	< 0.001	.05
4. Rumination	.94	90.35	22.27	84.08	21.99	94.05	21.65	13.99	< 0.001	.05
5. Depression	.90	4.61	4.84	4.30	4.46	4.79	5.06	.67	.41	< 0.01
6. Anxiety	.85	4.62	4.46	3.92	3.99	5.03	4.68	4.13	.04	.01

Note. PSU = Problematic smartphone use.

2.3. Analysis

We used R software 3.6.1 (R Core Team, 2019) for data cleaning and preliminary analysis. We implemented R's *mice* package to impute trivial (<5%) missing responses using maximum likelihood (ML) procedures, subsequently computing scale scores. We used R's *fmsb* (coefficient alphas), *pastecs* (descriptives), *careless* (insufficient responding), *ez* (ANOVA effects), and *corrplot* (bivariate correlations) packages. All continuous variables were normally distributed.

We used Mplus 8.3 for LCA based on PSU items, implementing ML estimation with robust standard errors (Maydeu-Olivares, 2017), treating PSU items as continuously-scaled. We tested various unconditional (i.e., without covariates) LCA models (e.g., 1 class, 2 classes, etc.), compared using the Lo-Mendell-Rubin likelihood ratio chi-square test (LMR), and adjusted LMR (aLMR). Statistically significant LMR/aLMR tests support a model with K rather than K-1 classes (Tein et al., 2013). Additional fit indices considered were the Bayesian Information Criterion (BIC), and sample size-adjusted version (aBIC), indicating better fit with smaller values, and entropy (representing correct classification) (Tein et al., 2013).

After selecting the best fitting model, we added covariates of latent class membership, featured in Fig. 1: sex and summed scores on depression, anxiety, rumination, positive and negative smartphone use expectancies. We used logistic regression to model covariate effects on class membership using Mplus' three-step (Vermunt) method to account for misclassification from posterior probability estimation (Collier and Leite, 2017).

3. Results

Bivariate intercorrelations among summed continuous-scaled covariates and PSU scores are displayed in Fig. 2. Scale descriptive statistics are in Table 1, also displaying sex differences. All scales were intercorrelated ($p < 0.05$) except for positive expectancies with anxiety severity. Women scored higher than men on several scales, with small effect sizes.

Table 2 shows unconditional LCA results for 1- through 4-class models. Neither LMR nor aLMR were statistically significant after 2 classes, indicating that a more complex model did not enhance fit. We primarily used these indices as a basis for selecting the 2-class model as best-fitting (H1), being most objective than other indices. Entropy was also optimal in the 2-class model, which correctly classified 97% of Class 2 and 98% of Class 1′s participants. BIC values were more favorable for models with more classes, however. Thus, we did not have unanimous support for a 2-class model. In evaluating this model against a 3-class model, however, the latter model essentially split the 2-class model's milder class into two very parallel subclasses based on severity, not distinguishable qualitatively. A 4-class model split off a small ($n = 13$) extreme class from the 2-class model's severe class, quite parallel to each other (results available upon request).

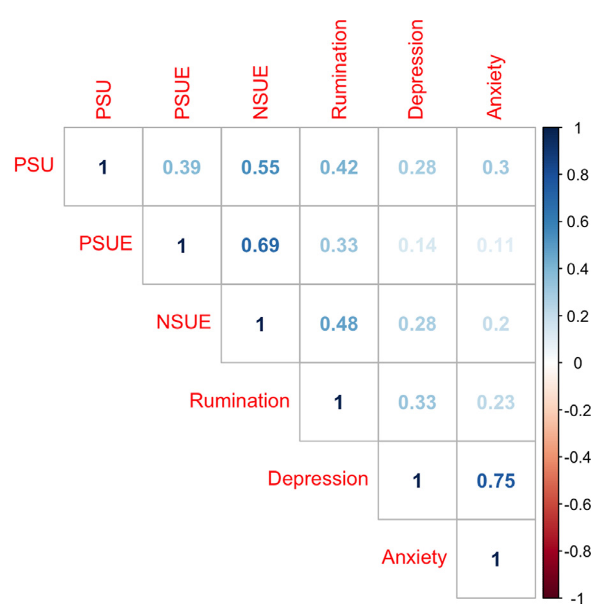

Fig. 2. Pearson correlation matrix of primary variables.
Note. PSU = Problematic smartphone use; PSUE = Positive smartphone use expectancies; NSUE = Negative smartphone use expectancies; RUM = Rumination; DEP = Depression; ANX = Anxiety. All correlations were positive. Correlations with a darker shade indicate stronger correlations. All correlations were $p <$ .001, except for PSUE-DEP (p = .02) and PSUE-ANX (p = .07).

Table 2
PSU item latent class analysis model comparisons.

# of Classes	BIC	aBIC	Entropy	LMR	p	aLMR	p
1	10,212.99	1049.57	N/A	N/A	N/A	N/A	N/A
2	**9604.82**	**9506.52**	**.92**	**670.38**	**<0.001**	**659.77**	**<0.001**
3	9464.26	9331.07	.84	202.79	.08	199.58	.08
4	9435.18	9267.12	.87	91.29	.06	89.84	.07

Note. PSU = Problematic smartphone use; BIC = Bayesian Information Criterion; aBIC = Adjusted Bayesian Information Criterion; LMR = Lo-Mendell-Rubin Likelihood Ratio Test Value; aLMR = Adjusted LMR; N/A = Not Applicable (not possible to estimate for a one-class model).

Fig. 3 displays classes based on item severity. Class 2 ($n = 89$) is the more severe class, with especially sharp differences from the milder Class 1 ($n = 197$) on withdrawal symptoms - that is, being impatient/fretful without one's smartphone, having one's phone always in mind when separated from it, and not imagining decreased phone use despite affecting daily life.

Finally, Table 3 displays covariate effects on the 2-class model. Only rumination (H2) and negative smartphone use expectancies (H4) were significant (positively associated with the more severe class), adjusting for other covariates. Anxiety and depression severity (H3), positive expectancies (H4), and sex were not significant.

4. Discussion

We explored latent subgroups of participants based on PSU severity ratings. We found most support for a 2-class model (H1), representing mild and more severe profiles. This model is similar to the 3-class model of PSU items found by Elhai et al. (2019b), but combines their more symptomatic two classes into a single class. A 2-class solution was also found in Elhai and Contractor (2018), examining smartphone use frequency (rather than PSU) items.

Though some parallelism was evident between the classes in Fig. 3, there were especially sharp between-class differences on withdrawal symptoms, suggesting that these classes do not merely differ across the board on symptom severity. Instead, the difference on withdrawal symptoms suggests that withdrawal may be a key dimension discriminating between subsets of smartphone users assessed for PSU symptoms. Earlier reviews suggested little evidence in the literature supporting smartphone-based withdrawal symptoms (Billieux et al., 2015). However, more recent empirical work has found that when separated from one's smartphone, some participants (especially more frequent smartphone users) evidence withdrawal symptoms including increased psychological distress (Wilcockson et al., 2018), and even behavioral indicators including increased heart rate and blood pressure (Cheever et al., 2014; Clayton et al., 2015). As smartphones have become more widely accepted as part of necessarily daily life, withdrawal upon phone separation may be a more prevalent phenomenon than in the past, and a more salient indicator of the PSU construct.

We found that rumination was positively related to the more

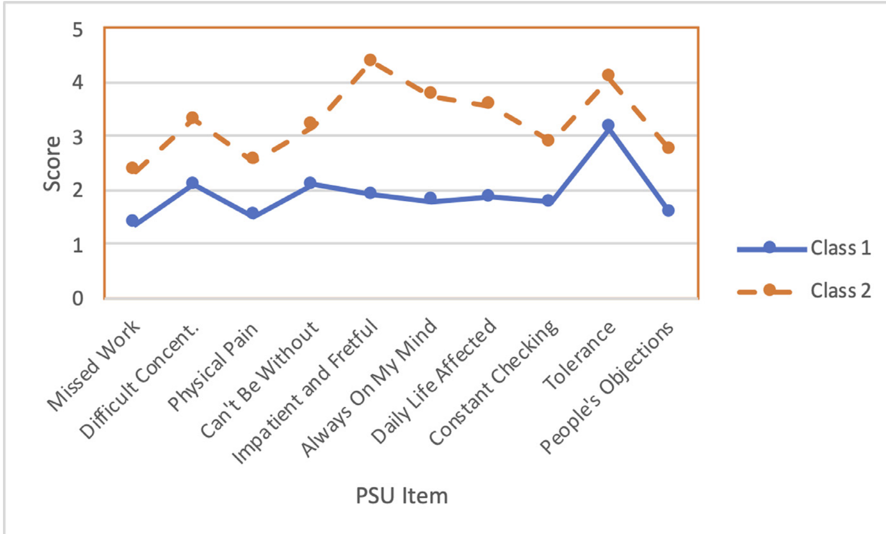

Fig. 3. The 2-class PSU latent class analysis model with standardized mean scores.
Note. PSU = Problematic smartphone use. Class 1′s $n = 197$, and Class 2′s $n = 89$.

Table 3
PSU latent class membership and relations with covariates using logistic regression and the three-step method.

Covariate	B	SE of B	z	p	Odds ratio
Sex	−0.02	.33	−0.05	.96	.98
Positive Smartphone Use Expectancies	.08	.05	1.49	.14	1.08
Negative Smartphone Use Expectancies	.10	.05	2.16	.03	1.10
Rumination	.02	.01	2.55	.01	1.02
Depression	.05	.05	1.07	.29	1.06
Anxiety	.08	.05	1.60	.11	1.08

Note: PSU = Problematic smartphone use.

symptomatic PSU class (H2). Rumination was associated with PSU severity in prior work (Liu et al., 2017; Elhai et al., 2018b, 2020; Liu et al., press). And Elhai et al. (2019b) found a similar construct, worry, related to more severe PSU latent class membership. In fact, worry and rumination are related constructs involving repetitive negative thinking, with rumination involving past events, and worry involving future events (Ehring and Watkins, 2008). Rumination may drive some individuals – especially those predisposed to depressive or anxiety disorders – to engage in PSU through excessive communication on messaging and social media apps with signficant others and loved ones, aiming to seek reassurance and self-worth (Billieux et al., 2015; Elhai et al., 2019c). Improving mental health among individuals engaging in PSU will therefore not only involve technological solutions to decrease excessive use, but also psychotherapeutic interventions to boost perceived social support (Hogan et al., 2002), as social support is key to psychological functioning (De Silva et al., 2005). Our result fits with I-PACE (Brand et al., 2019) in conceptualizing responses to predisposing variables - specifically dysfunctional coping - as influencing PSU severity.

Anxiety and depression are related to PSU severity (reviewed by Thomée, 2018; Elhai et al., 2019a), and we discovered such significant relationships in bivariate analysis (Fig. 2), consistent with I-PACE. Yet, in contrast to response variables, depressive and anxious symptoms were less bivariately correlated with, and not related in covariate-adjusted LCA, with PSU levels (rejecting H3). This finding supports recent research demonstrating that in contrast to background psychopathology variables, response variables in I-PACE may be more important to PSU severity. This result was observed for response variables including FOMO, emotion dysregulation, rumination, and boredom proneness (Oberst et al., 2017; Elhai et al., 2018a, 2018b, 2018c; Wolniewicz et al., 2018; Gül et al., 2019). Perhaps response variables are more proximal to current functioning and thus have a greater day-to-day influence on PSU symptoms. Response variables may also represent current, salient stress that activates diathesis from underlying psychopathology (Belsky and Pluess, 2009).

Prior research has discovered that positive and negative internet use expectancies relate to PIU severity (Brand et al., 2014; Wegmann et al., 2015; Wegmann and Brand, 2016, 2017; Stodt et al., 2018). However, these studies only reported bivariate rather than multivariate adjusted relationships for positive and negative expectancies. We too found both positive and negative expectancies (regarding smartphone use) bivariately related to PSU severity, but in covariate-adjusted LCA, only negative expectancies were significant (H4). This finding fits with I-PACE's conceptualization of cognitive bias influencing PIU. The relative importance of negative over positive expectances to PSU fits more with negative than positive reinforcement models of addiction (Robinson and Berridge, 2003), recently discussed in context of PIU (Wegmann and Brand, 2019).

This study adds to the limited, newer research finding heterogeneity of PSU symptoms using LCA. This finding is important because it suggests that there may not be a single profile of PSU symptoms; a notion often ignored in correlational studies of PSU. Additionally, our results support the important role of internet-related cognitive bias and dysfunctional ruminative coping, as responses to psychopathology that correlate with severe PSU levels. Limitations include use of a college student sample which may not represent the larger population. We used a cross-sectional design, and therefore causation cannot be inferred from correlational results. Future research should use objective smartphone use logs in repeated measures designs to study relations with psychological variables (Rozgonjuk et al., 2018; Montag et al., 2019a). Finally, we mention that the smartphone itself is not the likely culprit in PSU. PSU arises from excessive use of applications installed on phones (hence content matters), in particular social media apps (Montag et al., 2015; Sha et al., 2019), and Freemium games (Montag et al., 2019b).

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Contributors

JE and AD led the project. JE and AD designed the study protocol. JE and AD conducted data management, and JE conducted data analyses. JE wrote the initial manuscript, and HY and CM substantially revised the manuscript. JE and AD had full access to the data.

CRediT authorship contribution statement

Jon D. Elhai: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft. **Haibo Yang:** Writing - review & editing. **Abigail E. Dempsey:** Conceptualization, Data curation, Methodology, Project administration. **Christian Montag:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors report no conflicts of interest with this paper's study.

Outside the scope of the present paper, Dr. Elhai notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; is a paid, visiting scientist at Tianjin Normal University; occasionally serves as a paid, expert witness on PTSD legal cases; and receives grant research funding from the U.S. National Institutes of Health and Department of Defense.

Dr. Montag has received (to Ulm University and earlier University of Bonn) grants from the German Research Foundation (DFG) and the German Federal Ministry for Research and Education. Dr. Montag has performed grant reviews for several agencies; has edited journal sections and articles; has given academic lectures in clinical or scientific venues or companies; and has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties, but never from the gaming or social media industry.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2020.112845.

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