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Examining latent classes of smartphone users: Relations with psychopathology and problematic smartphone use

Jon D. Elhai [a, b, *], Ateka A. Contractor [c]

[a] Department of Psychology, University of Toledo, 2801 W. Bancroft Street, Toledo, OH, 43606, USA
[b] Department of Psychiatry, University of Toledo, 3065 Arlington Avenue, Toledo, OH, 43614, USA
[c] Department of Psychology, University of North Texas, 1155 Union Circle, Denton, TX, 76203, USA

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A B S T R A C T

Little is known about how people use their smartphones, and whether usage patterns are related to psychopathology and problematic smartphone use. We sampled 296 college students, and administered self-report scales to assess frequency of using various smartphone features, and problematic smartphone use. We also assessed psychopathology constructs (ruminative thinking and emotion regulation deficits), and demographics (age and gender) as potential covariates of smartphone use patterns. Using latent class analysis, we identified two distinct classes of smartphone feature use, with one class representing especially *heavy use* (particularly that of social networking, audio and visual entertainment, and image- and video-taking), and the other class involving *light use* (particularly that of social networking, audio entertainment and image- and video-taking). Higher levels of rumination, and higher levels of cognitive reappraisal as an emotion regulation strategy, were related to the heavy use class. The heavy use class scored higher on all problematic smartphone use outcome variables. Results aid in understanding the nature and relation of smartphone usage patterns to psychopathology and problematic smartphone usage.

1. Introduction

Despite the productivity advantages of using a smartphone, its excessive use has become a concern in modern society. “Problematic smartphone use” (PSU) involves excessive use of a smartphone with associated symptoms observed in substance and addictive disorders, such as social or work interference, and withdrawal symptoms when unable to use one's phone (Billieux, Maurage, Lopez-Fernandez, Kuss, & Griffiths, 2015a). PSU is associated with adverse consequences such as distracted driving (Cazzulino, Burke, Muller, Arbogast, & Upperman, 2014), physical health problems such as musculoskeletal pain (Xie, Szeto, Dai, & Madeleine, 2016; İNal, Demİrcİ, Çetİntürk, Akgönül, & Savaş, 2015), academic difficulties (Samaha & Hawi, 2016; Seo, Park, Kim, & Park, 2016), and mental health problems (reviewed in Elhai, Dvorak, Levine, & Hall, 2017a). However, little is known about the heterogeneity of ways in which people use their smartphones, and how such heterogeneity differentially relates to PSU.

Psychopathology is associated with PSU. In a recent paper, Elhai et al. (2017a) systematically reviewed the most widely studied psychopathology variables for relations with PSU: depression, anxiety, stress, and low self-esteem. The authors discovered that depression and anxiety severity demonstrated moderate and small associations (respectively) with smartphone use frequency and PSU. However, effect sizes for anxiety were small on average, and depression severity was sometimes non-significant or inversely related to PSU (Augner & Hacker, 2012; Elhai, Levine, Dvorak, & Hall, 2016, 2017c; J. Kim, Seo, & David, 2015). Studying more contemporary psychopathology constructs may aid in understanding what drives PSU.

Some contemporary psychopathology constructs that have become increasingly important in recent psychopathology research are “transdiagnostic”— that is, those constructs that cut across numerous mental disorders. Such constructs play a substantial role in the development and maintenance of mental disorders (Mansell, Harvey, Watkins, & Shafran, 2008), and are also clinical targets in psychological interventions across various mental disorders (Hofmann, Sawyer, Fang, & Asnaani, 2012). Two important

* Corresponding author. University of Toledo, 2801 W. Bancroft St., Mail Stop 948, Toledo, OH, 43560, USA.
E-mail address: contact@jon-elhai.com (J.D. Elhai).

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transdiagnostic constructs are emotion regulation and rumination.

Emotion regulation is the process by which people regulate their emotions to adapt to their environment. Adaptive emotion regulation involves two distinct processes - higher cognitive reappraisal, and lower expressive suppression (Gross, 1998). Cognitive reappraisal involves reinterpreting negative emotional stimuli in a non-emotional, cognitive manner, while expressive suppression involves inhibiting negative emotion (Tull & Aldao, 2015). Elhai et al. (2016) found in a community sample that expressive suppression was related to higher levels of PSU, and cognitive reappraisal was related to smartphone use frequency.

Another transdiagnostic construct, rumination, is a maladaptive method of regulating negative emotion by overemphasizing negative thoughts of oneself, rather than engaging in processing the negative emotion (Mennin & Fresco, 2013). Rumination is highly related to numerous types of psychopathology (Aldao, Nolen-Hoeksema, & Schweizer, 2010). Rumination has been conceptualized to contribute to problematic internet use (Davis, 2001). Finally, Elhai, Tiamiyu, and Weeks (in press) discovered in a college student sample that after adjusting for age, gender, and other psychopathology variables, rumination was related to increased smartphone use and PSU.

Our interest was to examine types of smartphone use and their correlates with psychopathology at a more granular level, based on specific features of use. One method of such granular analysis is to empirically explore subgroups of research participants based on their reported patterns of use, through mixture modeling. Mixture modeling is a statistical method for empirically uncovering heterogeneity among a sample of participants based on a set of observed variables (Masyn, 2013; McLachlan & Peel, 2000). One type of mixture model is latent class analysis (LCA), involving examination of cross-sectional, ordinal/categorical variables for distinct subgroups of individuals based on their responses (Muthén, 2008).

One previous paper used mixture modeling to study smartphone usage patterns. Hamka, Bouwman, de Reuver, and Kroesen (2014) recruited a community sample of adults and inquired about types of smartphone uses (albeit, without assessing psychopathology or PSU). The authors found six latent classes of smartphone users including a) very minimal smartphone users, b) basic users with limited smartphone app use, c) average users with moderate amounts of app and web use, d) information seekers with heavy amounts of web searching, but low app use, e) users with extensive app use, and f) users with high use of web utilities but low use of installed apps. However, the authors did not examine contemporary psychopathology constructs as predictor variables, nor was PSU included in the analyses.

1.1. Theory

There are several reasons and motives for using a smartphone. Some reasons include enhancing productivity (e.g., with reminders and scheduling), information seeking (e.g., web searching and news browsing), social networking, relaxation (e.g., music), entertainment (e.g., movies), monetary compensation (e.g., locating consumer deals), and personal status enhancement (Dhir, Chen, & Nieminen, 2015; van Deursen, Bolle, Hegner, & Kommers, 2015). Additionally, several factors influence the acceptance and use of a smartphone, including perceptions of value, and quality with the following dimensions: performance/system, use and access, content, service, and experience (Shin, 2015; Shin, Shin, Choo, & Beom, 2011).

Uses and Gratifications Theory (UGT) is a mass communications theory aimed at explaining motivations for consuming mass media (Blumler, 1979), adapted to explain use of particular smartphone features (Grellhesl & Punyanunt-Carter, 2012; Wei & Lu, 2014). UGT assumes that differences across individuals drive them to have particular emotional needs to be gratified, and such needs influence their choices in consuming mass media. Background characteristics such as female gender, as well as psychological constructs such as depression, anxiety, negative affect, proneness to boredom, and behavioral activation have been supported in studies on UGT in explaining increased smartphone use (Dhir et al., 2015; Elhai, Levine, Dvorak, & Hall, 2017c; Elhai, Vasquez, Lustgarten, Levine, & Hall, in press; Grellhesl & Punyanunt-Carter, 2012; Park, Kim, Shon, & Shim, 2013; Wolniewicz, Tiamiyu, Weeks, & Elhai, in press).

One widely-used categorization of internet uses involves the distinction between social use vs. process (i.e., non-social) use (Song, LaRose, Eastin, & Lin, 2004), a categorization used in the smartphone use literature as well (Elhai et al., 2017c; van Deursen et al., 2015). Mixed results have been found regarding whether these broad types of smartphone use are differentially associated with levels of PSU. Some studies found that PSU was more related to social use (Lee, Chang, Lin, & Cheng, 2014; Lopez-Fernandez, Honrubia-Serrano, Freixa-Blanxart, & Gibson, 2014; Zhitomirsky-Geffet & Blau, 2016), while other studies supported non-social use (Elhai, Hall, Levine, & Dvorak, 2017b; Elhai et al., 2017c; van Deursen et al., 2015).

An additional theory, Compensatory Internet Use Theory (CIUT) (Kardefelt-Winther, 2014), could be viewed as an extension of UGT. CIUT proposes that people attempt to alleviate their negative emotion by using (or overusing) technology. Thus in CIUT, negative emotion (an individual difference variable) can be viewed as the antecedent to technology (e.g., smartphone) use. And increased or excessive technology use is viewed as the compensatory behavior aimed at regulating negative emotion. Several studies thus far have supported CIUT in explaining PSU (Elhai, Tiamiyu, & Weeks, in press; Long et al., 2016; Wang, Wang, Gaskin, & Wang, 2015; Wolniewicz et al., in press; Zhitomirsky-Geffet & Blau, 2016).

Thus in UGT and CIUT, psychopathology can be conceptualized as motivating increased and excessive smartphone use. And such increased use can be conceptualized as a strategy for compensating for and regulating psychopathology.

1.2. Research model

Prior studies have used research models that would fit with UGT and CIUT in explaining PSU. Such models have used demographic and psychopathology variables to explain increased frequency of smartphone use. In turn, smartphone frequency is modeled to explain PSU, because increased use is conceptualized to translate into problematic use (Oulasvirta, Rattenbury, Ma, & Raita, 2012; van Deursen et al., 2015). Such integrated models of demographics, psychopathology, smartphone use frequency and problematic use have been tested and supported in recent papers (Elhai et al., 2017c; Elhai, Tiamiyu, & Weeks, in press; J. Kim et al., 2015; J.-H. Kim, 2017; van Deursen et al., 2015).

We used a similar model in the present paper, though with different statistical methods (See Fig. 1). We measured smartphone use frequency with LCA, to uncover latent subgroups of individuals based on their reported frequency of using various smartphone features. We modeled proximal demographic covariates of the smartphone use LCA, including age and gender. Younger people engage in more smartphone use compared to older people (Lu et al., 2011; van Deursen et al., 2015). Furthermore, women use smartphones more frequently than men do (Jeong, Kim, Yum, & Hwang, 2016; Wang et al., 2015). We also included psychopathology-related proximal covariates of the smartphone use LCA, including emotion regulation deficits and rumination. Finally, we modeled PSU using several PSU subscales as the dependent variables associated with the smartphone use LCA.

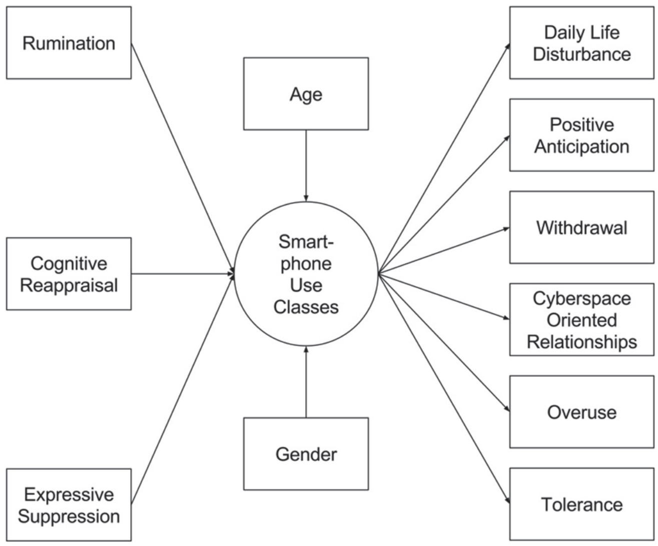

Fig. 1. Structural model of demographic and psychopathology covariates, latent class analysis, and problematic smartphone use outcomes.

1.3. Hypotheses

We posed several hypotheses based on theory and prior empirical findings.

1) Higher levels of rumination will be associated with the heavier smartphone use class(es) discovered in LCA.

Rumination is conceptualized as a maladaptive coping strategy for processing emotion (Mennin & Fresco, 2013). As such, rumination can be considered an individual difference variable in UGT (Blumler, 1979), and an antecedent psychopathology construct to excess internet use in CIUT (Kardefelt-Winther, 2014), for which increased smartphone use would be the consequential compensatory behavior. Rumination has demonstrated relations with increased smartphone use after adjusting for age, gender, and other psychopathology variables (Elhai, Tiamiyu, & Weeks, in press).

2) Higher levels of expressive suppression, and lower levels of cognitive reappraisal (emotion regulation facets), will be associated with the heavier smartphone use class(es).

Using more suppression and less reappraisal is considered maladaptive in the process of regulating negative emotion (Gross, 1998). Therefore, increased suppression and decreased reappraisal can be regarded as individual difference variables within UGT, and antecedent psychopathology constructs within CIUT, for which increased smartphone use is a compensatory behavior. Elhai et al. (2016) found in a community sample that expressive suppression was related to PSU and mediated relations between depression and PSU. Elhai et al. (2016) also found that higher reappraisal was related to increased smartphone use, though contradictory to theory. Finally, emotion regulation deficits have been related to problematic social media use (Hormes, Kearns, & Timko, 2014).

3) Heavier smartphone use class(es) will evidence higher scores on all PSU subscales.

Increased use of a smartphone is conceptualized to drive PSU (Oulasvirta et al., 2012; van Deursen et al., 2015), evident in prevailing models of PSU (Elhai et al., 2017c; Elhai, Tiamiyu, & Weeks, in press; J. Kim et al., 2015; J.-H. Kim, 2017; van Deursen et al., 2015). Elhai et al. (2017b) found in a community sample that all tested subscales of PSU were related to increased social and/or process smartphone use in bivariate analyses; subscales involving functional disturbance, excitement from and excessive use of a smartphone were significant in multivariate analyses.

2. Method

2.1. Procedure

We recruited 305 participants from a Midwestern university's undergraduate psychology research pool in 2016. Participants signed up for the study based on viewing it on the university's Sona Systems web portal for available research studies. We advertised this study as a 20- to 30-min internet survey regarding “use of electronic devices, and your emotions.” Signing up for the study routed participants to an online consent statement and web survey. We removed two participants from this study for not indicating gender (a covariate), and seven participants for missing more than half the items on at least one questionnaire used in analyses. The resulting 296 participants served as the effective sample.

2.2. Participants

In the sample of 296 participants, average age was 19.44 (SD = 2.16). Most participants were women (n = 227, 76.7%). The majority identified as Caucasian (n = 234, 79.3%), with some representation from African-American (n = 34, 11.5%), Hispanic/Latino (n = 14, 4.7%), and Asian-American (n = 12, 4.1%) ethnicities (endorsements were not mutually-exclusive). Most participants were freshman (n = 137, 49.7%) or sophomores (n = 98, 33.1%). Employment status was mostly part-time (n = 147, 49.7%), with some participants employed full-time (n = 19, 6.4%).

2.3. Measures

2.3.1. Demographics

We inquired about such demographic characteristics as age, gender, ethnicity and employment.

2.3.2. Smartphone use

We used a scale measuring frequency of 11 types of smartphone features, developed by Elhai et al. (2016). We used a Likert-type scale for items, ranging from “1 = Never” to “6 = Very Often.” The queried features included “Voice/video calls (making and receiving),” “Texting/instant messaging (sending and receiving),” “Email (sending and receiving),” “Social networking sites,” “Internet/websites,” “Music/podcasts/radio,” “Games,” “Taking pictures or videos,” “"Watching video/TV/movies,” “Reading books/magazines,” and “Maps/navigation.” Elhai et al. (2016) discovered this scale to be reliable, and with moderate correlations with Kwon et al.'s (2013) Smartphone Addiction Scale. Internal consistency in the present sample was 0.76.

2.3.3. Smartphone Addiction Scale (SAS)

We used Kwon et al.'s (2013) SAS which measures severity of PSU. The SAS has 33 items ranging from “1 = Strongly disagree” to “6 = Strongly agree.” It has six subscales including “Daily life disturbance,” “Positive anticipation,” “Withdrawal,” “Cyberspace oriented relationships,” “Overuse,” and “Tolerance.” The SAS has demonstrated reliability, and convergent validity against other scales measuring PSU and problematic internet use (Chotpitayasunondh & Douglas, 2016; Demirci, Orhan, Demirdas, Akpinar, & Sert, 2014; Kwon et al., 2013). In the present sample, internal consistency was 0.93 for the total scale, and ranged from 0.74 (Daily life disturbance) to 0.87 (Positive anticipation) for the subscales.

2.3.4. Emotion regulation scale (ERQ)

The ERQ (Gross & John, 2003) is a 10-item self-report measure of emotion regulation, with subscales of cognitive reappraisal and expressive suppression. Response options range from "1 = Strongly disagree" to "7 = Strongly agree." The ERQ has demonstrated good reliability for its subscales, with convergent validity against measures of rumination, depression, anxiety, stress and coping (Gross & John, 2003; Spaapen, Waters, Brummer, Stopa, & Bucks, 2014). Internal consistency in the present sample was 0.89 for cognitive reappraisal, and 0.75 for expressive suppression.

2.3.5. Ruminative Thought Style Questionnaire (RTSQ)

The RTSQ (Brinker & Dozois, 2009) is a self-report measure of ruminative thinking. It includes 20 items on a Likert-type scale of "1 = Does not describe me at all" to "7 = Describes me very well." The RTSQ has demonstrated reliability, and convergent validity with similar scales (Brinker & Dozois, 2009; Tanner, Voon, Hasking, & Martin, 2012). Internal consistency in the present sample was 0.95.

2.4. Analysis

Small amounts of missing item-level data were observed for the measures; approximately 7% of the sample missed an average of 1–2 items for a given scale. We used maximum likelihood (ML) estimation procedures to estimate missing item-level data (Graham, 2009). After estimating missing values, we summed item responses to derive scale scores.

We used Mplus Version 8 to estimate the LCA based on smartphone use feature responses. These items are on an ordinal scale, and therefore we treated them as ordinal variables in LCA. We conducted the LCA using ML with robust standard errors (Yuan & Bentler, 2000). We examined the adjusted Lo-Mendell-Rubin likelihood ratio chi-square test (aLMR), where a model with K classes is compared to a model with K-1 classes (Nylund, Asparouhov, & Muthén, 2007). Statistical significance in aLMR for the model with one additional class indicates better fit for that model. We also examined the Bayesian Information Criterion (BIC; and its sample size-adjusted version, aBIC), and entropy (indicating quality of correct classification) (Nylund et al., 2007). A model that is at least ten points lower on BIC/aBIC is the preferred model, with an odds of 150:1 (Raftery, 1995).

We next added age, gender, and summed scores for cognitive reappraisal, expressive suppression and rumination as proximal covariates of latent class membership. Logistic regression analysis was used for regressing the latent class variable on the covariates. As distal dependent variables of latent class membership, we regressed SAS subscales on the LCA variable. Using the approach discussed by others (Asparouhov & Muthén, 2014; Lanza, Tan, & Bray, 2013), we used Mplus' three-step method to estimate the latent class variable based on posterior probabilities, regressing SAS subscales while taking into account misclassification from posterior probability estimation.

3. Results

3.1. Descriptive statistics

Rumination total scores averaged 91.61 (SD = 23.73). Emotion regulation summed scores averaged 15.20 (SD = 5.26) for Expressive Suppression, and 28.14 (SD = 7.26) for Cognitive Reappraisal. PSU summed scores averaged 12.32 (SD = 5.04) for Daily Life Disturbance, 23.80 (SD = 7.42) for Positive Anticipation, 17.18 (SD = 6.19) for Withdrawal, 16.93 (SD = 5.81) for Cyberspace Oriented Relationships, 14.87 (SD = 4.83) for Overuse, and 8.43 (SD = 3.48) for Tolerance. The sum of smartphone frequency items averaged 48.25 (SD = 7.63). A correlation matrix of these scale scores, along with age and gender, is presented in Table 1. Frequency data for using smartphone features are found in Table 2. The most frequently endorsed (as "Very Often") smartphone features were text and instant messaging (74.7%), social networking (64.9%), internet (58.8%), music/podcasts/radio (50.7%), and taking pictures and video (40.9%).

3.2. Primary LCA results

Table 3 details LCA results (without covariates) for models ranging from 1 to 4 classes. aLMR, the most objective of these indices (Nylund et al., 2007), was not statistically significant after 2 classes, indicating that model fit was not improved with more complex models. Evidence for a 2-class model was also supported by this model having the lowest BIC Value; and by a precipitous drop in aBIC after a 1-class model, with substantial plateauing after 2 classes. Entropy was 0.83, and correct classification was 96% for Class 1, and 95% for Class 2.

Fig. 2 displays the latent classes, and probabilities of endorsing the most frequent use category ("Very Often") for each smartphone use type. Class 1 appears to represent especially high users of social networking, listening and viewing entertainment, picture- and video-taking (labelled *high users*). Class 2 involves much less use of smartphone features across the board, but with lighter use most represented by social networking, listening entertainment, and taking pictures and videos (labelled *light users*).

3.3. LCA covariate and outcome results

Rumination and Cognitive Reappraisal were significant covariates of the latent class variable, as indicated in Fig. 3. The odds ratio was 1.02 for Rumination, indicating that each increase of one point for the Rumination scale was associated a 2% increased likelihood of being classified in Class 1 (*high users*). The odds ratio was 1.05 for Cognitive Reappraisal, indicating that each increased point for Cognitive Reappraisal was associated with a 5% increased likelihood of being classified in Class 1. Neither age, gender, nor Expressive Suppression were significant covariates. The two latent classes were significantly different on all PSU outcome scales. As detailed in Table 4, Class 1 scored higher on all PSU scales.

4. Discussion

In this study, we empirically examined smartphone use typologies in a sample of college students, using a theoretical model with demographic and psychopathology covariates, and PSU as the outcome. We found support for two distinct latent classes of smartphone users based on their endorsements of types of smartphone use, predicted by higher levels of both rumination and cognitive reappraisal. These classes significantly differed on subscales measuring PSU.

Very little prior research has examined typologies of smartphone use. In contrast to Hamka et al. (2014) who examined primarily messaging, website and social networking features, our study examined a wider range of smartphone features – we analyzed a total of 11 features. We found two latent classes of smartphone users, including a) heavy users, especially of social networking sites, audio and visual entertainment, and b) light

Table 1
Correlation matrix of study variables.

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Age											
2. Gender	$-.13^{*}$										
3. Rumination	$-.07$	$.21^{***}$									
4. Suppression	.05	$-.11$	$.15^{*}$								
5. Reappraisal	$-.10$	.06	.07	$.24^{***}$							
6. SUF	$-.20^{***}$	$.24^{***}$	$.22^{***}$	.01	$.23^{***}$						
7. SAS DLD	$-.06$	$.13^{*}$	$.31^{***}$	.07	$-.04$	$.17^{**}$					
8. SAS PA	$-.14^{*}$	.09	$.23^{***}$	$.14^{*}$	$.14^{*}$	$.26^{***}$	$.38^{***}$				
9. SAS Withdrawal	$-.11$	.10	$.33^{***}$	.05	.03	$.28^{***}$	$.46^{***}$	$.65^{***}$			
10. SAS COR	$-.06$	$.15^{*}$	$.23^{***}$	$.24^{***}$	.10	$.28^{***}$	$.39^{***}$	$.58^{***}$	$.61^{***}$		
11. SAS Overuse	.03	.10	$.37^{***}$	.05	$.12^{*}$	$.27^{***}$	$.51^{***}$	$.46^{***}$	$.53^{***}$	$.46^{***}$	
12. SAS Tolerance	$-.08$	$.14^{*}$	$.28^{***}$	$.20^{***}$	$.14^{*}$	$.24^{***}$	$.55^{***}$	$.46^{***}$	$.49^{***}$	$.52^{***}$	$.56^{***}$

Note: SUF=Smartphone Use Frequency; SAS=Smartphone Addiction Scale; DLD = Daily Life Disturbance; PA=Positive Anticipation; COR=Cyberspace Oriented Relationships. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 2
Frequency of using smartphone features.

Smartphone Feature	"Never"	"Rarely"	"Occasionally"	"Somewhat Often"	"Often"	"Very Often"
Voice/Video Calls	8	29	52	74	72	61
Text/Instant Messaging	0	2	10	21	42	221
Email	10	36	51	68	77	54
Social Networking	3	6	20	22	53	192
Internet	0	4	18	22	78	174
Music/Podcasts	5	10	24	42	65	150
Gaming	28	98	70	36	34	30
Pictures/Video	1	15	27	57	75	121
Watching TV/Movies	26	45	53	38	56	78
Reading	81	87	61	36	15	16
Maps/Navigation	6	27	67	78	68	50

N = 296.

Table 3
Latent class analysis model comparisons.

# of Classes	BIC	aBIC	Entropy	aLMR	p
1	9550.90	9382.82	N/A	N/A	N/A
2	9323.09	8983.75	.83	533.19	<.001
3	9426.45	8915.87	.88	203.25	.77
4	9576.52	8894.68	.91	156.70	.85

Note: BIC=Bayesian Information Criterion; aBIC = Adjusted Bayesian Information Criterion; aLMR = Adjusted Lo-Mendell-Rubin Likelihood Ratio Test Value; p = aLMR's p value; N/A = Not Applicable (not possible to estimate for a one-class model).

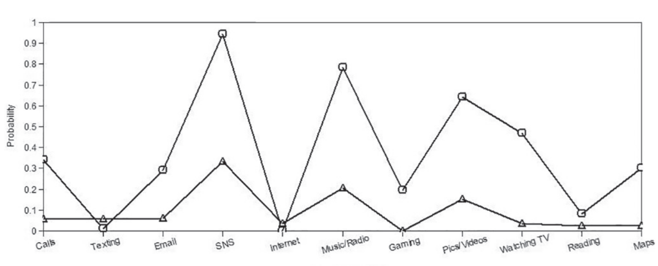

Fig. 2. The 2-Class LCA. Note. Class 1 (n = 156) is denoted by the line series with circles. Class 2 (n = 140) is denoted by the line series with triangles. The Y Axis indicates the probability of endorsing the highest response option ("Very Often") for the given smartphone feature.

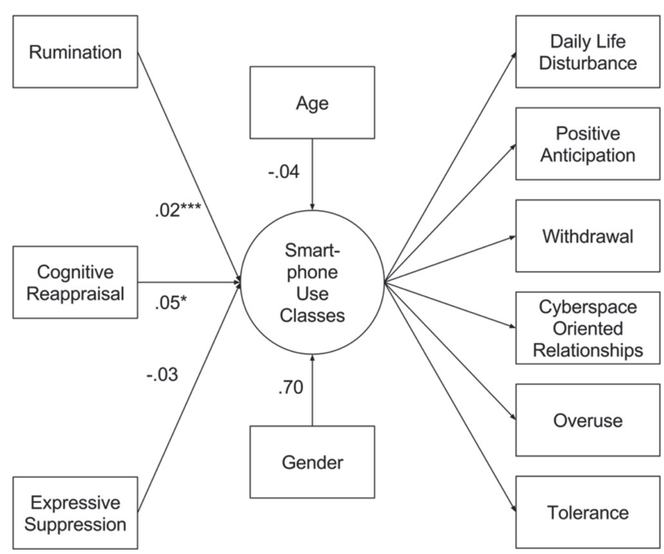

Fig. 3. Structural Model of Demographic and Psychopathology Covariates, Latent Class Analysis, and Problematic Smartphone Use Outcomes: With Estimates for Covariates. Notes. Estimates shown are unstandardized logistic path (beta) coefficients. Estimates for the outcome (SAS) variables are displayed in Table 4. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

users, whose light use primarily involved social networking sites, audio entertainment, and taking pictures and videos. Our study, thus, supports the heterogeneity embedded in the amount and types of smartphone use characterized by two distinct subgroups of smartphone users.

We found support for Hypothesis 1. Higher levels of rumination were related to the heavier smartphone use class. This finding fits well with UGT (Blumler, 1979) in assuming that individual difference variables such as rumination would drive a particular type of media use – in this case, smartphone use. Our finding also fits well with CIUT (Kardefelt-Winther, 2014), which would conceptualize

Table 4
Latent class membership differences on outcome variables.

SAS Scale	Class 1 M	SE of M	Class 2 M	SE of M	Chi-square	p
Daily Life Disturbance	13.08	.43	1.45	.42	6.75	.01
Positive Anticipation	25.58	.64	21.73	.59	18.06	<.001
Withdrawal	18.69	.55	15.44	.46	18.79	<.001
Cyber Oriented Relationships	18.20	.48	15.46	.50	14.54	<.001
Overuse	16.36	.40	13.15	.40	30.44	<.001
Tolerance	9.31	.32	7.41	.26	19.30	<.001

increased smartphone use as a means of tempering negative emotion – in this case, ruminative thinking. This finding also fits with recent research revealing that rumination is associated with PSU, and also associated with increased smartphone use after adjusting for age, gender, and other psychopathology variables (depression and social anxiety) (Elhai, Tiamiyu, & Weeks, in press). Rumination may drive smartphone use and/or PSU, especially among those with depression, anxiety or poor emotion regulation skills. One possible mechanism for this relationship is that rumination in interpersonal relationships may be characterized by excessive reassurance seeking through checking one's phone for friends' notifications (Billieux et al., 2015b). Additionally, individuals with social anxiety and who ruminate about social interaction may avoid in-person social interaction, instead excessively using their smartphones or other online media (Elhai, Tiamiyu, & Weeks, in press; Wolniewicz et al., in press).

We failed to find support for Hypothesis 2. Contrary to this hypothesis, expressive suppression was not associated with membership in the higher smartphone use class. Also in contrast to Hypothesis 2, *higher* levels of cognitive reappraisal were associated with membership in the higher smartphone use class. Because cognitive reappraisal is an adaptive form of emotion regulation (Gross, 1998), based on UGT and CIUT, we would expect that *lower* levels of cognitive reappraisal would be associated with the heavy user class. This was not borne out in our findings, however. Nonetheless, these findings parallel those from Elhai et al. (2016) who analyzed data on emotion regulation, smartphone use and PSU, using a community sample. We must note that the present study, as well as Elhai et al. (2016), used cross-sectional data, and thus causality cannot be properly assessed. Being a heavy smartphone user could consequently drive individuals to cognitively reappraise excessive smartphone use as not being a waste of time. Longitudinal or repeated measures designs could help determine the nature of this association.

We found support for Hypothesis 3. The heavier smartphone use class scored higher across all subscales of PSU. This finding fits with existing theoretical models of PSU, whereby increased and habitual smartphone use is conceptualized specifically to grow into PSU (Oulasvirta et al., 2012; van Deursen et al., 2015). This model also fits with structural equation models supporting increased smartphone use as mediating relationships between psychopathology and PSU (Elhai et al., 2017c; Elhai, Tiamiyu, & Weeks, in press; J.; Kim et al., 2015; van Deursen et al., 2015). Thus, in attempting to understand the construct of PSU, it is important to recognize that several types of psychopathology can lead to increased or habitual use of a smartphone, as a means of regulating negative emotion with such technology use. And in turn, the habitual, increased use of a smartphone can grow into PSU, causing impairment in such areas as school, work or social interaction. Thus, psychopathology may be a risk factor for PSU, while habitual/increased smartphone use may be an important mechanism that can fuel the psychopathology-PSU relationship.

In fact, recent research has uncovered important and novel findings in understanding the relationships among psychopathology, increased smartphone use, and PSU. Until recently, the majority of relevant studies only examined levels of depression, anxiety, stress, or low self-esteem as types of psychopathology associated with PSU (reviewed in Elhai et al., 2017a). Newly published studies have examined and found support for additional types of psychopathology associated with PSU, including posttraumatic stress disorder (Contractor, Frankfurt, Weiss, & Elhai, 2017), rumination (Elhai, Tiamiyu, & Weeks, in press), emotion dysregulation (Elhai et al., 2016), self-regulation (Gökçearslan, Mumcu, Haşlaman, & Çevik, 2016), proneness to boredom (Elhai, Vasquez, et al., in press), behavioral activation (Elhai et al., 2016; Y.; Kim et al., 2016), and fear of social evaluation (Wolniewicz et al., in press). Many of these new studies have examined and revealed support for smartphone use frequency as a mediating variable between psychopathology and PSU. This trend in recent research expanding the types of psychopathology examined in relation to PSU is encouraging, in order to better understand PSU as a construct.

The present study has several limitations. First, data collected were cross-sectional, so causality between variables cannot be determined. Future research would benefit from repeated measures or longitudinal analysis to explore associations between psychopathology, smartphone use and PSU - a type of design rarely used in the literature, with few exceptions (Jun 2016; Lu, Katoh, Chen, Nagata, & Kitamura, 2014; Thomee, Härenstam, & Hagberg, 2011). Studies would also benefit from using objectively collected smartphone data in conjunction with psychopathology variables (Elhai, Tiamiyu, Weeks, et al., in press; Faurholt-Jepsen et al., 2016), as self-reported smartphone use is not completely accurate when validated against objective use logs (Boase & Ling, 2013; Kobayashi & Boase, 2012). Finally, the present study's reliance on a college student sample is a limitation as well.

Nonetheless, this study is one of the first to empirically examine the typology of smartphone use, and also integrate psychopathology correlates and PSU into the analysis. Our findings indicate the need to consider the heterogeneity embedded in the amount and types of smartphone use in future research. Clinically, it would be important to consider emotional regulation skills and PSU as intervention targets for those presenting with heavy smartphone use (particularly social networking and entertainment related uses). Future research could examine a similar research question using momentary and real-time assessments to capture more nuanced smartphone use typologies.

In conclusion, distinct patterns of usage may characterize how individuals use the features of their smartphones. The pattern of such smartphone usage may be related to specific types of psychopathology, such as a ruminative thinking style. The pattern of use also appears related to several dimensions of PSU.

Disclosure section

No competing financial interests exist.