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Rumination, Excessive Reassurance Seeking, Depression, and Problematic Social Media Use

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Abstract

Depression and problematic social media use (PSMU) symptoms are robustly correlated. However, few studies have investigated cognitive or affective psychological mechanisms explaining why depressed individuals may develop PSMU. We analyzed cross-sectional web survey data collected from 388 American university students in 2025. We administered standardized measures of depression, rumination, excessive reassurance seeking (ERS; a maladaptive interpersonal strategy often used by depressed individuals to test social relationship strength), and problematic social media use. Using confirmatory factor analysis, we discovered good-fitting measurement models for these measures. Using structural equation modeling, we found that rumination's brooding dimension was significantly related to both ERS and PSMU symptoms. ERS was also associated with PSMU severity. Analyses revealed that brooding indirectly accounted for relations between depression and PSMU severity. Furthermore, ERS accounted for relations between brooding and PSMU severity. Finally, we discovered that the path from brooding to ERS indirectly accounted for relations between depression and PSMU. Results provide support for cognitive/affective and coping mechanisms such as rumination and ERS that may explain relationships between depression and PSMU. We also place findings in context of a widely-studied theoretical model of problematic Internet use.

Keywords: depression; rumination; excessive reassurance seeking; problematic social media use

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Introduction

Problematic Social Media Use, Its Consequences, and Associations With Psychopathology and Cognitive/Affective Variables

Problematic social media use (PSMU) involves prolonged, uncontrolled social media use, and requires adverse consequences to daily functioning (Cataldo et al., 2022; Moretta & Wegmann, 2025). PSMU is a specific type of more general problematic Internet use (PIU), focusing on social media overuse (Montag et al., 2021). We provide

the caveat that PSMU is not a diagnosable mental disorder in the Diagnostic and Statistical Manual of Mental Disorders-5-TR (DSM-5-TR; American Psychiatric Association, 2022) or International Classification of Diseases-11 (ICD-11); World Health Organization, 2019). Furthermore, researchers often prefer using the term PSMU over addiction-related terminology such as "social media addiction" (Casale, 2020; Demetrovics et al., in press; Montag et al., 2025). We should emphasize that PSMU may involve diverse symptom presentations, and diverse sets of risk factors underlying its development (Orfi & Ellithorpe, 2026).

Despite not being a diagnosable disorder, PSMU's (potential) adverse consequences are substantial. For example, PSMU can result in impairments in academic functioning among students (Salari et al., 2025). PSMU also results in impaired occupational performance (Kelber et al., 2024).

Several psychopathology-related variables are robustly correlated with PSMU symptoms. Specifically, negative affectivity (i.e., negative, unpleasant emotion), such as depression, anxiety, and low self-esteem, have robust relationships with PSMU symptoms across studies, with pooled (Pearson's *r*) effect sizes of .31, .31, and −.24, respectively (Jing et al., 2025). We should emphasize that negative affectivity can influence PSMU, but PSMU can also subsequently exacerbate negative affectivity. However, current evidence suggests that mental disorders are more likely to precede rather than result from PSMU (Elhai et al., 2026). Most theoretical frameworks in fact assume and conceptualize that poor mental health influences PIU, but with reciprocal effects possible (Brand et al., 2019; Caplan, 2003; Kardefelt-Winther, 2014). For example, the Interaction of Person-Affect-Cognition-Execution (I-PACE) model conceptualizes diverse dispositional variables such as psychopathology and negative affectivity, along with more proximal risk and resilience factors, for developing and maintaining PIU (Brand et al., 2016); we discuss this framework in more detail in the Theory section, below. Recent work with Chinese college students is consistent with depression preceding PSMU (but effects are complex; Li & Li, 2024). However, some work has nonetheless discovered PSMU driving subsequent negative affectivity, in adult Bangladeshi social media users (Ahmed et al., 2025) and in a nationally representative sample of Finish social media users (Marttila et al., 2021).

Numerous studies have investigated cognitive and affective risk factors for PSMU (Wegmann & Brand, 2021). Cognitive and affective risk factors for PIU in general also fit within the I-PACE model, and can include such diverse constructs as emotion dysregulation, coping styles, Internet-related cognitive biases, executive dysfunction, craving, and numerous others. Furthermore, cognitive/affective mechanisms account for relations between depression and PSMU severity, including distress intolerance examined in U.S. college students (Shanthi et al., 2025) and Chinese adults recruited online (Yao et al., 2023), meta-cognitions about social media use investigated in Australian adults recruited online (Meynadier et al., 2026), online social comparison studied in Australian college students (Samra et al., 2022), loneliness studied in Chinese college students (Chen et al., 2022) and Iranian healthcare patients (Lin et al., 2021), decreased perceived social support in Chinese college students (Chen et al., 2022), and attentional bias in Chinese secondary school students (Xiao et al., 2022).

Rumination

Another cognitive/affective variable associated with PSMU symptoms is rumination (reviewed in Castro-Calvo et al., 2022; F. Gao & Du, 2025). Rumination also accounted for associations between depression and PSMU symptoms in Indian college students (Mitra & Rangaswamy, 2019) and Chinese adolescents (Wang et al., 2018). Rumination involves repetitive negative thinking, focusing primarily on past events, as a maladaptive emotion regulation strategy (Rickerby et al., 2024). Rumination is a risk factor for depressive/anxiety disorders (Olatunji et al., 2013), with some evidence for depression/anxiety driving rumination, as well as reciprocal relationships (Hasegawa et al., 2014; Nolen-Hoeksema et al., 2007). Two rumination dimensions specifically have been widely studied: a) brooding, involving gloomy/moody pondering, considered a more maladaptive type of rumination, and b) reflection, defined as analytical introspection about emotion, considered less maladaptive (Rickerby et al., 2024). Highly ruminative individuals may engage in PSMU a) to distract themselves from ruminative thoughts (Castro-Calvo et al., 2022), and b) to over-engage in online reassurance behaviors (e.g., messaging, and social media use) to alleviate their rumination (Billieux et al., 2015).

Excessive Reassurance Seeking

In fact, excessive reassurance seeking (ERS) is another potential contributing factor to PSMU. Depression often co-occurs with significant interpersonal difficulties (reviewed in Bird et al., 2018). Consequently, depressed individuals

often excessively seek reassurance from friends/family to test relationship strength (Evraire & Dozois, 2011). However, such relationship testing can inadvertently worsen relationships, thus maintaining one's depression and isolation (Joiner et al., 1999).

Modern-day ERS is often digitally-based, such as messaging to elicit a response (Billieux et al., 2015), or seeking social media likes, comments, and follows from close associates or others (Forchuk et al., 2021). Thus, excessive reassurance seekers may consequently engage in PSMU as a means or behavioral manifestation of ERS. However, ERS can nonetheless still involve offline reassurance behaviors. Furthermore, research demonstrates that rumination about interpersonal relationships can influence ERS for relationship testing (Grant et al., 2013; Weinstock & Whisman, 2006). Although not specifically examining PSMU, Mitchell and Hussain (2018) recruited adult social media users and revealed a moderate relationship between general ERS (not online-specific ERS) and problematic smartphone use (PSU) severity. Additionally, Elhai et al. (2020) discovered in American college students that general ERS was associated with PSU severity, and ERS accounted for relations between rumination and PSU. Furthermore, Elhai et al. (2020) discovered a serial indirect effect: depression influenced rumination, which in turn predicted ERS, in turn influencing PSU symptoms. Thus, the association between rumination and ERS may account for relations between depression and PIU (e.g., PSU or PSMU).

Despite existing research studies examining PSMU's relations with such cognitive and affective variables as rumination and ERS, prior work has not examined a comprehensive model exploring relations among these variables. We therefore aimed to fill this gap by examining how rumination and ERS correlate with PSMU, while also incorporating depression as a covariate.

Theory

Numerous theories have been conceived to explain the development and maintenance of PIU (Tunney & Rooney, 2023). A notable theory is the I-PACE model, mentioned above. To elaborate on this model, I-PACE is a prominent, comprehensive theoretical framework for understanding development of PIU (e.g., PSMU) (Brand et al., 2016; Brand et al., 2019; Brand et al., 2025). I-PACE proposes dispositional, predisposing risk factors for PIU, such as biological (e.g., genetics), personality and temperament (e.g., neuroticism, impulsivity), attachment, deep seated cognitions, and psychopathology (e.g., depression and anxiety) variables. Such dispositional (including psychological) variables are associated with PIU (e.g., Giancola et al., 2026; Meynadier et al., 2024). I-PACE also conceptualizes various other, more proximal (less dispositional) risk factors for PIU that may be influenced by predisposing variables, including affective/cognitive responses (e.g., emotion dysregulation, attention bias), coping styles (e.g., avoidant coping), craving, desire thinking regarding Internet use, punishment sensitivity regarding avoiding emotional distress, executive dysfunction and disinhibition impairment, and Internet-related cognitive biases. These affective/cognitive variables are conceptualized in I-PACE as mechanisms through which dispositional variables may ultimately lead to PIU. Furthermore, the predisposing and more proximal variables can intersect or interact with each other to influence development of PIU. I-PACE also distinguishes between how these risk and resilience factors may lead to PIU (in a maladaptive way) in contrast to more healthy forms of Internet use. Furthermore, I-PACE distinguishes between risk factors influencing the initial development of PIU, as well as risk factors that maintain PIU over time (Brand et al., 2019). Thus I-PACE is a dynamic and comprehensive theoretical framework that conceptualizes a diverse set of risk and resilience variables to explain how people develop healthy or maladaptive Internet use patterns in the short- and long-term.

In I-PACE, depression would represent a predisposing, psychopathology-related risk factor of PSMU, in which the motivation behind social media use (and PSMU) is to alleviate negative affect (although often can exacerbate negative affect). Rumination would represent a more proximal risk factor of PSMU, as an affective/cognitive mechanism. ERS would also serve as a more proximal risk factor for PSMU, as a coping style.

Aims and Hypotheses

Our aim was to examine relations between depression, ERS, rumination and PSMU symptoms, testing a theoretically-driven research model linking these variables. We should emphasize that our measurement of ERS was not specific to online-based reassurance seeking behaviors; rather, we queried ERS more generally.

We posed several hypotheses.

H1: *ERS should be positively associated with PSMU severity*.

Individuals engaging in ERS may use and overuse social media to seek reassurance, which can result in PSMU. Prior work discovered ERS significantly related to PSU severity (Elhai et al., 2020; Mitchell & Hussain, 2018). This hypothesis has not been examined regarding PSMU. However, PSU and PSMU are robustly related (Rozgonjuk et al., 2020; Rozgonjuk et al., 2021), because most social media use occurs on the smartphone (Marino et al., 2021). Thus, we expected that findings from this work with PSU could potentially extend to PSMU, in light of the inherently interpersonal and feedback-oriented nature of social media platforms.

H2: *Rumination - specifically the brooding dimension - should be positively associated with PSMU severity*.

Rumination is consistently related to PSMU severity (Castro-Calvo et al., 2022; F. Gao & Du, 2025). Because the brooding dimension is considered the most maladaptive form of rumination (Rickerby et al., 2024) and is characterized by a passive focus on negative affect, it may be particularly relevant to maladaptive coping behaviors such as PSMU (L. Gao et al., 2021). Therefore, brooding should be especially strongly associated with PSMU severity.

H3: *ERS should account for relations between rumination's brooding dimension and PSMU severity*.

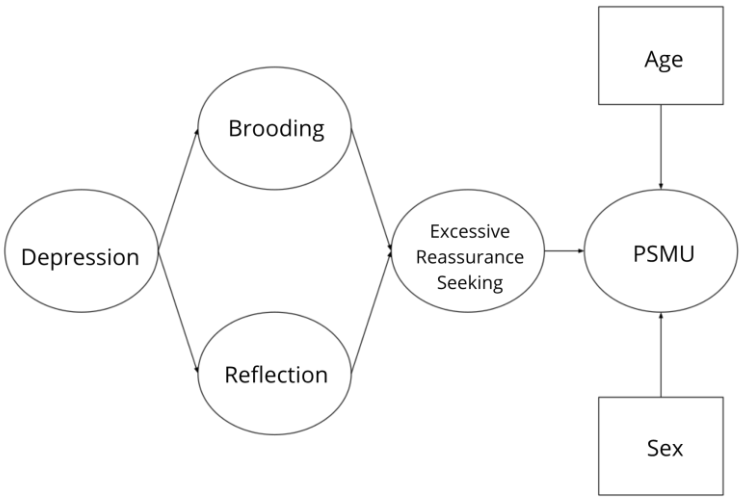
Rumination about interpersonal relationships can co-occur with ERS aimed at relationship testing (Elhai et al., 2020; Grant et al., 2013; Weinstock & Whisman, 2006). And ERS can consequently function as a mechanism linking rumination to greater PSMU severity (see H1). In fact, Elhai et al. (2020) discovered that ERS accounted for relations between rumination and PSU severity; we expect that this finding could extend to PSMU.

H4: *A serial indirect effect should be apparent, such that depression is associated with rumination's brooding dimension, in turn associated with ERS, and consequently related to PSMU severity*.

Evidence for a serial indirect effect begins with support for depression and rumination being highly correlated (Olatunji et al., 2013), with some longitudinal evidence pointing to depression symptoms preceding increases in later rumination (Hasegawa et al., 2014; Nolen-Hoeksema et al., 2007). Next, rumination may be associated with ERS for relationship testing (Elhai et al., 2020; Grant et al., 2013; Weinstock & Whisman, 2006). And as indicated in H1, ERS is associated with PSU (Elhai et al., 2020; Mitchell & Hussain, 2018), and could be associated with the similar PSMU variable. Furthermore, Elhai et al. (2020) discovered a serial indirect effect from depression to rumination to ERS to PSU symptom severity, suggesting broader emotion regulation and interpersonal mechanisms that may be particularly salient in social media contexts and warrant examination with PSMU.

Research Model

Figure 1. *Hypothesized Research Model Diagram (Model A).*



Note. PSMU = Problematic social media use. Oval-shaped variables are latent variables, while rectangle-shaped variables are observed variables. Factor loadings paths for the latent variables are not displayed, to reduce visual clutter.

Figure 1 displays our initial research model (Model A). Depression is specified to predict rumination's brooding and reflection dimensions. Brooding and reflection are specified to predict ERS. And ERS is specified to predict PSMU severity. This model fits with I-PACE's conceptualization of predisposing psychopathology variables (e.g.,

depression) influencing cognitive/affective response variables and coping style (e.g., rumination and ERS), in turn representing risk factors for PSMU (Brand et al., 2019; Brand et al., 2016). We modeled age and sex at birth as covariates of PSMU, because of consistent relationships for PSMU severity with both younger age and female sex (Cheng et al., 2021). We also tested additional model variations discussed below.

Methods

We collected data from January to December 2025, during spring and fall classes at a medium-sized university in the Midwestern USA. We recruited participants enrolled in Introductory Psychology courses using the Department of Psychology's Sona Systems research pool. Participants were required to be a minimum age of 18, and course research points were awarded for participation. Participation required agreeing to terms in an online informed consent form; if consenting, participants were routed to a web survey on psychdata.com. The university's Institutional Review Board first approved the study. The research project was not preregistered.

Initially, 422 participants appeared to have participated, providing survey responses. We subsequently removed data for the following reasons: 14 participants for answering few or no questions after initial demographic query, six duplicate participants (judged by reconciling duplicate names provided on a separate web form with timestamps), four improbably fast completers (in the fastest 1% rank for time duration, or <215 seconds, for the larger survey of which we present relevant measures below), six underage participants, one participant consecutively answering 23 questions with the same response, and three participants denying current social media use. Our final sample included 388 participants.

Average age was 20.06 years (*SD* = 4.18); age ranged from 18–61, however the vast majority were <26 years old (*n* = 373, 96.1%). A majority reported their biological sex as female (*n* = 255; 65.7%). A minority identified gender as non-binary or transgender (*n* = 8, 2.1%). Although more than two-thirds of participants reported Caucasian race (*n* = 271; 69.8%), we also had Black (*n* = 61; 15.7%), Asian (*n* = 57; 14.7%), and Hispanic/Latino (*n* = 36; 9.4%) minority representation (percentages add to >100% because multiple responses could be selected). A slight majority were first-year university students (*n* = 228; 58.8%). Most participants were working part-time (*n* = 205; 52.8%), or not working (*n* = 138; 35.6%).

Measures

We administered a web survey using cross-sectional methodology as part of a larger research project. In addition to demographic inquiry, the following measures relevant to this particular paper's study were administered (in English).

Social Media Use

We asked participants "Do you currently use at least one social networking/social media site? (e.g. Facebook, Instagram, Twitter, Snapchat, Discord, Tiktok, WhatsApp, Pinterest, Reddit, etc.)." Participants responded with a *yes* or *no* answer; only those selecting *yes* were included in analyses (also mentioned above).

Depression Anxiety Stress Scale-21 (DASS-21)

We administered the DASS-21 (Lovibond & Lovibond, 1995), including 21 items measuring depression, anxiety and stress. The DASS-21 response scale ranges from 0 (*did not apply to me at all/never*) to 3 (*applied to me very much, or most of the time/almost always*). We used a past-month rating time-frame. Zanon et al. (2021) presented comprehensive analyses demonstrating the DASS-21's psychometric properties. We only analyzed the seven depression items, summed for a depression score. Our sample's coefficient alpha for depression was .90; Omega was .92. We present item numbers for the DASS-21's depression items in Supplemental Table S3.

Ruminative Responses Scale-10 (RRS-10)

The RRS-10 (Treynor et al., 2003) measures rumination, using ten items, with a response scale of 1 (*almost never*) to 4 (*almost always*). No time-frame is provided. We separately evaluated the five brooding and five reflection items, summing them for subscale scores. Psychometrics are detailed in Valencia and Paredes-Angeles (2022). Our

coefficient alpha was .82 (Omega = .86) for brooding items, .79 (Omega = .84) for reflection, and .87 (Omega = .90) for the whole measure. Item numbers for the subscales are displayed in Supplemental Table S2.

Threat-Related Reassurance Seeking Scale (TRRS)

The original TRRS (Cougle et al., 2012) measures ERS, and has eight items, with a response scale from 1 (*no, not at all*) to 7 (*yes, very much*). No rating time-frame is provided. We modeled the four "general threat" items and summed them for a total score, revealing associations with negative affectivity measures (Clark et al., 2021). Our coefficient alpha was .85 (Omega = .88). Item numbers for these four items (within the 8-item TRSS) are displayed in Supplemental Table S4.

Bergen Social Media Addiction Scale (BSMAS)

The BSMAS (Andreassen et al., 2016) measures PSMU, including six items, with a response scale from 1 (*very rarely*) to 5 (*very often*). We used a past-month time-frame for inquiry. This measure was only administered to participants indicating current social media use, as mentioned above. We summed items for a total score. Recent work has detailed adequate psychometric properties (Bottaro et al., 2026). Our coefficient alpha was .85 (Omega = .90).

Analysis

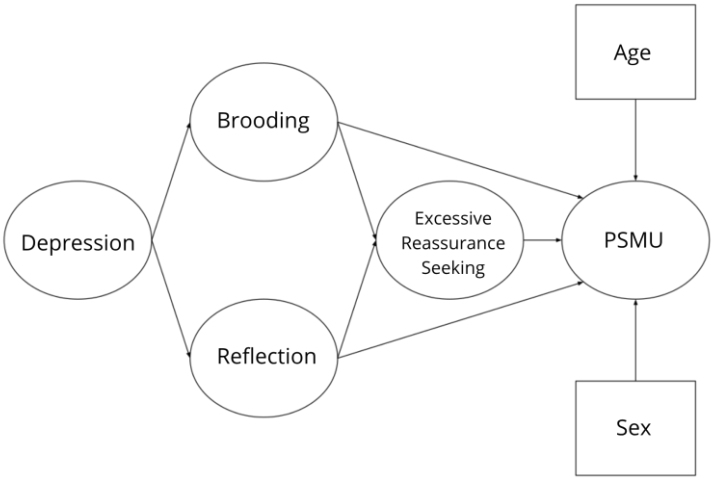
We used R software V.4.2.5 (through RStudio) for data cleaning and preliminary analyses. After data exclusions discussed above, we had trivial amounts of missing data: 0.40% of item-level data were missing. Using R's *mice* package, we imputed missing item-level data within a scale (one scale at a time) for participants with at least 50% of their item responses present. Using this procedure, 1-3 missing items were imputed for 2-37 participants per scale, contingent on the scale (see Supplemental Table 6 for details). Subsequently, we summed scale/subscale scores, and had a complete dataset without missing scale scores. We used several additional R packages, for careless response detection (*careless*), missing data screening (naniar), internal consistency (*GPArotation*), descriptive statistics (*pastecs*), correlations (*apaTables*), and ANOVA (*sjstats*, *car*).

Next, we used R software to analyze means and standard deviations for continuous data (age and scale scores), and frequencies for categorical demographic variables. We computed Pearson correlations among age and scale scores. We used analysis of variance (ANOVA) with type III sum of squares to assess relations between sex and scale scores. The only skewed continuous variable was age (skewness = 6.36, kurtosis = 51.01), because of our truncated age range: more than 90% of participants were between age 18-23 (as expected for university students).

We used Mplus V.9 software to compute confirmatory factor analyses (CFA) for each measure separately. We modeled single-factor CFA models for depression, ERS, and PSMU; we modeled a two-factor (brooding and reflection) CFA model for rumination. Other than the TRSS, the remaining measures each use < 6 response options. Furthermore, all measures (including the TRRS) use descriptive, behavioral anchors for response options. Thus, the ratings scales more closely appear ordinal than continuous. Consequently, we treated items as ordinal in CFA, implementing weighted least squares estimation with a mean- and variance-adjusted (WLSMV) chi-square, using a polychoric covariance matrix, and probit- rather than linear-based factor loadings (Verhulst & Neale, 2021). We did not implement any residual error covariances, and the first unstandardized factor loading per scale was fixed to 1. We judged good model fit using established benchmarks, including values > .95 for the Tucker-Lewis index (TLI) and comparative fit index (CFI), < .06 for the root mean square error of approximation (RMSEA), and < .08 for the standardized root mean squared residual (SRMR), with mild worsening of goodness-of-fit suggestive of adequate rather than good fit (Xia & Yang, 2019). However, because we treated items as ordinal, we highlight that RMSEA is not sensitive to detecting good model fit with ordinal data (Shi et al., 2020).

Next, we used Mplus software to test our initial research model from Figure 1 (Model A) using structural equation modeling (SEM) with WLSMV estimation. All variables were modeled as latent factors using CFA, except for age and sex observed covariates. We used the same estimation procedures as in CFA above. We also tested an alternative model (Figure 2) by adding paths from the rumination factors directly to PSMU. We used chi-square difference testing with a correction factor using Mplus' DIFFTEST command to statistically compare model fit between these models; we also compared CFI values to determine the magnitude of fit difference between models (Cheung & Lau, 2011).

Figure 2. *Model B Diagram.*



Note. PSMU = Problematic social media use. Oval-shaped variables are latent variables, while rectangle-shaped variables are observed variables. Factor loadings paths for the latent variables are not displayed, to reduce visual clutter.

Finally, we tested indirect effects by computing cross-products of our direct path coefficients, and using the Delta method to determine standard errors of these indirect effects. We used non-parametric bootstrapping with 1,000 replications (using Mplus' bootstrap command) to facilitate more accurate indirect effect standard errors (MacKinnon et al., 2007), dividing them by the direct path coefficients to compute z-tests and p values. We used WLSMV estimation for these analyses.

We present our anonymized data for the CFA and SEM analyses, along with our survey protocol, in a data repository. The data can be accessed using the following link: https://data.mendeley.com/datasets/7z5tzwxj8f/1

Results

Table 1 displays descriptive statistics, and intercorrelations, for age and scale scores. The scales all had moderate-to-large intercorrelations. Age did not significantly correlate with most scales. Table 2 displays scale score descriptive statistics separated by sex, and tests of sex differences; several sex differences were found, but based on effect sizes, only ERS had greater than a small sex difference in magnitude, with women scoring significantly higher than men.

Table 1. *Means, Standard Deviations, and Pearson Correlations for Age and the Observed Scale and Subscale Scores.*

Variable	*M*	*SD*	1	2	3	4	5
Age	20.06	4.18					
PSMU	15.14	5.37	−.12*				
Depression	4.98	4.36	−.02	.31***			
ERS	15.80	6.09	−.04	.39***	.35***		
Brooding	11.51	3.69	−.05	.35***	.53***	.44***	
Reflection	10.88	3.55	−.03	.27***	.45***	.29***	.61***

Note. M and *SD* are used to represent mean and standard deviation, respectively. ERS = Excessive reassurance seeking; PSMU = Problematic social media use. * indicates $p < .05$. ** indicates $p < .01$. *** indicates $p < .001$.

Table 2. *Sex Differences for Scale/Subscale Scores Using Analyses of Variance (ANOVA).*

Variable	Men (*M*)	Men (*SD*)	Women (*M*)	Women (*SD*)	*F*(1,386)	*p*	η^2
PSMU	13.684	5.186	15.902	5.310	15.490	< .001	.040
Depression	5.143	4.484	4.902	4.296	0.267	.606	< .001
ERS	13.594	6.062	16.953	5.784	28.520	< .001	.070
Brooding	10.774	3.357	11.890	3.801	8.146	.005	.020
Reflection	10.729	3.387	10.957	3.641	0.358	.550	< .001

Note. M = Mean; *SD* = Standard deviation; *F* = ANOVA F test; *p* = *p* value or significance level; η^2 = eta-squared (effect size) value; PSMU = Problematic social media use; ERS = Excessive reassurance seeking.

Table 3 displays CFA results for constructs analyzed as part of Model A. Except for RMSEA (discussed above), CFA models mostly demonstrated evidence for good fit. Supplementary Tables S1-S4 display factor loadings for each CFA model. All standardized factor loadings were computed using Mplus' STDYX standardization method.

Table 3. *Confirmatory Factor Analysis (CFA) Results for Model A.*

CFA Model	$\chi^2(df)$, p	CFI	TLI	RMSEA (90% CI)	SRMR
Depression	54.652(14), $p < .001$	.992	.988	.087 (.063, .111)	.023
Rumination	175.366(34), $p < .001$	.959	.946	.104 (.089, .119)	.046
ERS	41.513(2), $p < .001$	.986	.958	.226 (.169, .288)	.020
PSMU	90.610(9), $p < .001$	.962	.937	.153 (.125, .182)	.038

Note. ERS = Excessive reassurance seeking; PSMU = Problematic social media use. χ^2 = chi-square value; *df* = degrees of freedom; *p* = *p* value/level of statistical significance; CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean squared error of approximation; SRMR = standardized root mean square residual; CI = confidence interval. All models used weighted least squares estimation with a mean- and variance- adjusted chi-square.

In conducting SEM, Model A (Figure 1) fit adequately, WLSMV $\chi^2(371) = 1106.269$, $p < .001$, CFI = .930, TLI = .924, RMSEA = .071 [90% CI: .067, .076], SRMR = .085. Model B (Figure 2), adding paths directly from rumination's brooding and reflection factors to PSMU, also resulted in adequate fit, WLSMV $\chi^2(369) = 1016.021$, $p < .001$, CFI = .939, TLI = .933, RMSEA = .067 [90% CI: .062, .072], SRMR = .081. Model B fit significantly better than Model A, DIFFTEST $\chi^2_{diff}(2) = 36.723$, $p < .001$; Model B's CFI increase of .009 points closely approached the .010 difference level typically considered substantial or meaningful in model testing (Cheung & Lau, 2011).

Because Model B fit better than Model A, we display the full output for Model B's direct path coefficients – see Table 4 (top portion). Depression was significantly associated with both brooding and reflection. Brooding (but not reflection) was significantly associated with ERS. Brooding (but not reflection) was significantly related to PSMU (after adjusting for ERS, age and sex), supporting H2. And ERS was significantly related to PSMU (after adjusting for brooding, reflection, age and sex), supporting H1.

Table 4. *Direct and Indirect Effect Standardized Results For Model B.*

	Std. Beta	*SE*	*Z*-test	*p*	Std. Beta 95% CI
Direct Effects					
ERS→PSMU	.261	0.059	4.411	< .001	
Brooding→PSMU	.225	0.061	3.690	< .001	
Reflection→PSMU	.094	0.053	1.769	.077	
Brooding→ERS	.475	0.052	9.121	< .001	
Reflection→ERS	.096	0.056	1.729	.084	
Depression→Brooding	.802	0.029	27.639	< .001	
Depression→Reflection	.725	0.033	22.167	< .001	
Age→PSMU	−.082	0.052	−1.574	.116	
Sex→PSMU	.417	0.111	3.748	< .001	
Indirect Effects					
Depression→Reflection→PSMU	.068	0.044	1.532	.125	[−.005, .141]
Depression→Brooding→PSMU	.180	0.057	3.177	.001	[.087, .274]
Depression→ERS→PSMU	.000	0.000	N/A	N/A	N/A
Brooding→ERS→PSMU	.124	0.034	3.634	< .001	[.068, .180]
Reflection→ERS→PSMU	.025	0.019	1.353	.176	[−.005, .056]
Depression→Reflection→ERS→PSMU	.018	0.014	1.329	.184	[−.004, .041]
Depression→Brooding→ERS→PSMU	.099	0.029	3.456	.001	[−.052, .147]

Note. ERS = Excessive reassurance seeking; PSMU = Problematic social media use; Std. Beta = Standardized beta/regression coefficient; *SE* = Standard error; *Z*-test = Computation of Std. Beta/SE; *p* = *p* value or significance level; CI = Confidence interval (provided for indirect effects); N/A = Not applicable (because dividing the Std. Beta by an SE of zero cannot be computed). Indirect effects' standard errors were bootstrapped. All standardized beta coefficients were computed using Mplus' STDYX method, except for the path from sex→PSMU which used the STDY method because sex is a categorical predictor variable. Sex was coded 1 = male, 2 = female.

Table 4 (bottom portion) displays indirect effects from Model B. Brooding significantly accounted for relations between depression and PSMU severity. Furthermore, ERS indirectly accounted for associations between brooding and PSMU severity, supporting H3. Finally, a serial indirect association from depression to brooding to ERS to PSMU severity was significant, supporting H4.

Despite our conceptualization of depression influencing rumination (discussed above), many studies alternatively demonstrate that rumination may influence depression (Olatunji et al., 2013). Therefore, we also tested an additional model—Model C. In Model C, rather than specifying depression to predict rumination's brooding and reflection factors, we instead specified brooding and rumination predicting depression (Model C, displayed in Supplemental Figure S1). Aside from this modification, Model C is similar to Model B. However, this model sequence does not fit well conceptually with I-PACE ordering of variables suggesting depression as the predictor/predisposing variable. We present results of Model C in Supplemental Results Description 1 (SRD1) and Supplemental Table 5 (S5).

Discussion

We examined research models testing relations among depression, rumination's brooding and reflection dimensions, excessive reassurance seeking, and problematic social media use. Our primary finding was that rumination's brooding dimension and ERS serially accounted for relations between depression and PSMU severity. These findings provide support for brooding and ERS as mechanisms that can explain the robust relationships often found between depression and PSMU (reviewed in Jing et al., 2025).

Supporting H1, we discovered that excessive reassurance seeking was significantly associated with problematic social media use severity (within Model B, and within Model C which included a reversed sequence of brooding to depression). Prior work has revealed ERS related to PSU (Elhai et al., 2020; Mitchell & Hussain, 2018). The present paper extends this finding to PSMU. Individuals engaging in ERS may naturally gravitate to using their smartphone and social media to message close associates in hope of a response, and to seek follows, likes, shares, and comments (Billieux et al., 2015; Forchuk et al., 2021). In this way, excessive reassurance seeking may be considered a coping strategy (albeit maladaptive) in the I-PACE model (Brand et al., 2019) that can increase likelihood of developing problematic online behavior such as PSMU.

Our findings are consistent with H2, in that rumination's brooding dimension was significantly associated with problematic social media use severity (in Models B and C). Rumination's reflection dimension was associated with PSMU severity only in bivariate correlational analyses, but not in our structural models which adjusted for other variables. Rumination can be considered a cognitive/affective response variable in I-PACE, and may result in PSMU as a means of distracting oneself from rumination (Billieux et al., 2015), and/or through online reassurance behaviors to alleviate ruminative thoughts (Castro-Calvo et al., 2022). Rumination in general is widely associated with various forms of problematic Internet use, including PSMU (Castro-Calvo et al., 2022; F. Gao & Du, 2025). However, little work has more granularly examined types of rumination (i.e., brooding and reflection) to explore differential relationships with PIU (L. Gao et al., 2021). Our findings support the distinction between brooding and reflection, with brooding being more maladaptive (Rickerby et al., 2024). Thus, brooding fits within I-PACE as a cognitive/affective risk factor that may influence PSMU.

Results also demonstrate support for H3, in that excessive reassurance seeking accounted for relations between rumination's brooding dimension and problematic social media use severity (in Model B, but not Model C). Previously, this research question was only tested with PSU (but not PSMU) as the dependent variable, finding that ERS accounted for relations between overall rumination and PSU severity (Elhai et al., 2020). Rumination seems to influence PSMU (Castro-Calvo et al., 2022; F. Gao & Du, 2025), but ERS could be an important mechanism explaining why some people scoring high in rumination consequently engage in PSMU. Excessive reassurance seeking may be conceptualized as a maladaptive behavioral coping mechanism or response to the cognitive (non-behavioral) process of rumination. In social media contexts, social comparison has been linked to greater social media engagement (Eitan & Gazit, 2024), which may heighten interpersonal uncertainty, thereby increasing ERS that, in turn, are associated with greater PSMU severity. Thus, this finding provides further support for I-PACE's focus on cognitive/affective factors, such as ERS and rumination, intersecting with each other to influence excessive Internet use.

We also found support for H4, in that the serial indirect effect from depression to brooding to ERS to PSMU severity in Model B was significant. This similar serial indirect effect in Model C's reversed sequence - from brooding to

depression to ERS to PSMU - was also significant. In fact, portions of the serial indirect effects involving depression were also significant, including depression to brooding to PSMU (Model B), and depression to ERS to PSMU (Model C). These findings attest further to brooding and ERS as mechanisms explaining the depression-PSMU relationship. Although testing PSU instead of PSMU, Elhai et al. (2020) discovered a similar serial indirect effect. This serial indirect effect fits well within I-PACE, because coping and cognitive/affective responses (e.g., ERS and rumination) are conceptualized as mechanisms explaining why predisposing psychopathology (e.g., depression) may intersect with more proximal factors (e.g., rumination and ERS) to influence PIU (such as PSMU). Thus, the significant serial indirect effect also provides further support for I-PACE.

Our most important findings were that a) excessive reassurance seeking accounted for relations between brooding and PSMU severity, and b) the ERS-brooding relationship accounted for relations between depression and PSMU severity. Models such as I-PACE attempt to understand risk factors for PIU, and importantly why some individuals with predisposing psychopathology such as major depressive disorder consequently engage in PSMU while other depressed individuals do not engage in PSMU. This issue is also relevant to findings that depression's relationship with PSMU severity is only moderate in size rather than larger (Jing et al., 2025), and whether other important mechanisms may be responsible for this relationship. Our findings suggest that brooding and ERS may be important cognitive and affective mechanisms explaining why some depressed individuals engage in PSMU. Depression may influence PSMU especially among those individuals who score high in brooding and whose brooding triggers ERS behaviors to test their interpersonal relationships. These findings support cognitive and affective variables intersecting with and accounting for relations between predisposing psychopathology and PIU in the I-PACE model.

Theoretical and Practical Implications

Results fit with theoretical frameworks such as the I-PACE model, extending the model's focus on cognitive/affective risk factors for PIU to also include such cognitive/affective variables as ERS and rumination. Importantly, results add support for cognitive/affective variables intersecting with predisposing variables (i.e., depression) in accounting for relations with PIU, such as PSMU. Practical implications in intervening among individuals with PSMU include not only directly targeting problematic online behaviors, but also targeting predisposing variables such as depression and depressive disorders, which may be some of the root causes of PSMU (Elhai et al., 2026), using empirically-validated psychological treatments for depression (Cuijpers et al., 2016). Also important is the use of empirically-validated treatments targeting maladaptive cognitions involving the need for reassurance, using cognitive restructuring (Ezawa & Hollon, 2023).

Limitations

We acknowledge several limitations with the present study. First, our design was cross-sectional, and thus we cannot confidently infer cause and effect. We added reverse-specified analyses especially because of mixed findings on whether rumination influences depression or vice-versa (Hasegawa et al., 2014; Nolen-Hoeksema et al., 2007; Olatunji et al., 2013). And while most theoretical frameworks suggest poor mental health influences PIU (Brand et al., 2019; Caplan, 2003; Kardefelt-Winther, 2014), reciprocal effects may still be apparent (Shoshani et al., 2024; Thorisdottir et al., 2020). Thus, it is alternatively possible that PSMU may amplify rumination or ERS, for example, through such processes as online social comparison or habitual smartphone/social media checking behavior; PSMU may also reinforce and exacerbate ERS through online interpersonal relationship testing. Experimental or longitudinal designs can help better address causality and the temporal order of these variables. Additionally, should emphasize not all of our SEM models fit well. Also, our sample was limited in comprising only Midwestern American students (primarily young adults) from one university. We also only used self-report methods for assessing psychopathology; using structured diagnostic interviews to assess depressive disorders, for example, would be a more rigorous assessment method. Furthermore, our measure of ERS was a general measure of reassurance seeking behaviors, rather than being specific to online ERS. Additionally, we did not objectively measure social media or smartphone use (Sapci et al., 2021), which is important when querying time spent using the Internet (Parry et al., 2021).

Conclusions

Despite the limitations, our results provide further support for coping and cognitive/affective psychological mechanisms (i.e., excessive reassurance seeking and rumination) that can explain why many depressed individuals engage in problematic social media use. Our data screening procedures also represent strengths, such as excluding respondents completing the survey too quickly. Future research should explore additional mechanisms underlying relations between psychopathology and PSMU, such as the fear of missing out (FOMO) (Elhai, Casale, & Montag, 2025), emotion dysregulation (Hutcheson et al., 2025), and attentional bias (Xiao et al., 2022). More granular examination of psychopathology symptoms and psychological processes most related to PIU is also warranted (Alavinikoo et al., 2025; Elhai, Casale, & Bond, 2025). Furthermore, including an online-specific assessment of ERS (e.g., Harmon et al., 2022) in future research would be helpful in understanding the relationship between ERS and PSMU. Finally, replicating findings in a clinical sample in future research would enhance clinical relevance.

Conflict of Interest

The authors report no conflicts of interest with this paper's study. However, outside the scope of the present paper, the authors report the following…

JDE notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); occasionally serves as a paid, expert witness on PTSD legal cases.

CM has generated books or book chapters for publishers of mental health texts. For some of these activities he received royalties. Dr. Montag mentions that he was part of a discussion circle (Digitalität und Verantwortung: https://about.fb.com/de/news/h/gespraechskreis-digitalitaet-und-verantwortung/) debating ethical questions linked to social media, digitalization and society/democracy at Facebook. In this context, he received no salary for his activities.

Use of AI Services

The authors did not rely on any large language models or AI in this research project or article write-up.

Data Availability Statement

The anonymized data and survey protocol from this project are available in a Mendeley repository: https://data.mendeley.com/datasets/7z5tzwxj8f/1

Authors' Contribution

Jon D. Elhai: conceptualization, methodology, project administration, writing—original draft, final approval. **Tali Gazit:** conceptualization, methodology, writing—review & editing, final approval. **Christian Montag:** writing—review & editing, final approval.

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