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Mental disengagement mediates the effect of rumination on smartphone use: A latent growth curve analysis

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Abstract

Rumination has consistently been found to predict excessive smartphone use. However, a paucity of research has examined the mechanism that underlies this relation. Drawing on relevant theoretical accounts, we examined whether specific coping functions that can be fulfilled through smartphones—i.e., mental disengagement, problem-focused, and socioemotional coping—mediate, in parallel, the positive link between rumination and smartphone use. Using latent growth curve and structural equation modeling (N = 217), we found that only mental disengagement fully mediated the link between rumination and the intercept (i.e., initial baseline levels) of smartphone use, which was objectively quantified using screen time monitoring applications installed on smartphones. In addition, although rumination directly predicted the slope (i.e., longitudinal changes) of smartphone use, the indirect effects of rumination on the slope via the three coping functions did not reach significance. Our findings highlight the importance of a specific coping function—i.e., mental disengagement—via smartphones in explaining the complex relation between rumination and smartphone overuse. Further, our study underscores several methodological advances in studying smartphone use.

Keywords: objective smartphone use, rumination, mental disengagement, smartphone coping, latent growth curve

Word count: 170

Mental Disengagement Mediates the Effect of Rumination on Smartphone Use: A Latent Growth Curve Analysis

Smartphones facilitate speedy communication, boost productivity, and strengthen social connections when used with proper controls. As smartphone use becomes more prevalent and necessary, a growing body of research has focused on the consequences of excessive smartphone use. For instance, studies have consistently found that excessive smartphone use is related to poor sleep quality, unsafe driving, heightened stress and anxiety, greater risk of depression, and lowered well-being (e.g., Demirci et al., 2015; Rozgonjuk et al., 2018; Thomée, 2018). In response, there has been a surge in research that examines potential factors that predict excessive smartphone use, such as low self-control or high neuroticism (Billieux et al., 2015; Kim et al., 2016). In particular, rumination—one's tendency to think repetitively, uncontrollably, and intrusively about the possible causes and consequences of stressors (Nolen-Hoeksema et al., 2008)—has received growing attention as a risk factor for excessive smartphone use because it has been shown to be associated with multiple psychopathological outcomes (McLaughlin & Nolen-Hoeksema, 2011).

While rumination has consistently been found to be associated with excessive smartphone use (Elhai, Levine et al., 2018; Elhai & Contractor, 2018), less is known about the specific mechanism that underlies this link. Further, given that the majority of previous studies have used self-report measures extensively (Ellis, 2019), which are useful but error prone due to memory bias or social desirability issues (Andrews et al., 2015; Boase & Ling, 2013), it is essential that we investigate the mechanism by objectively quantifying smartphone use. More importantly, since most studies on the relation between rumination and smartphone use have been cross-sectional in nature (Ellis, 2019; Thomée, 2018), our understanding has been limited to the relation that unfolds within a short time period. Consequently, there is a dearth of insights into the influence of a person's ruminative tendency on their smartphone use over an extended period.

Building on uses and gratification theory (Blumler, 1979), we first aimed to investigate the longitudinal relation between rumination and changes in smartphone use over time using rigorous methods, i.e., latent growth curve and structural equation modeling. In doing so, we sought to provide strong empirical evidence on the predictive effect of individuals' rumination on smartphone use over time. Specifically, we objectively measured smartphone use over a prolonged period by employing relevant applications on smartphones. We also used a self-report measure of smartphone use to compare its validity against our objective measure of smartphone use. Second, we sought to investigate potential psychosocial mediators that explain the relation between rumination and smartphone use. To this end, drawing on the theoretical model of internet compensatory use (Kardefelt-Winther, 2014), we examined the mediating roles of specific coping functions—i.e., mental disengagement, problem-focused coping, and socioemotional coping—that can be facilitated by smartphone use. Accordingly, we pose two primary research questions: (a) does rumination entail changes in smartphone use over time? and (b) do specific coping functions indirectly influence the relations between rumination and smartphone use over time?

1.1 A psychosocial mechanism

A growing number of studies have demonstrated a significant relation between rumination and excessive smartphone use (Elhai, Levine et al., 2018; Elhai & Contractor, 2018). Little research, however, has been conducted on the psychological factors that mediate the link. Uses and gratifications theory (Blumler, 1979) posits that individuals actively adapt their use of media to achieve specific types of gratification. Therefore, ruminating individuals' smartphone overuse may signal adaptive efforts to cope with their ruminative needs. For instance, given that ruminators tend to experience depression and heightened anxiety (Nolen-Hoeksema et al., 2008), they may use their smartphones to actively seek socioemotional support. Indeed, past studies have shown that ruminative individuals experience heightened fear of missing out and demand excessive assurance from others (Elhai et al., 2020; Elhai, Levine et al., 2018). Thus, it is plausible that ruminators rely heavily on their smartphones to solicit such socioemotional support. Further, given that ruminators are prone to seek distractors to relieve incessant problem-related thoughts (Hilt & Pollak, 2012; Nolen-Hoeksema & Morrow, 1993), smartphones, as a rich multimedia device, can be a convenient tool to distract themselves from unremitting problem-related rumination (Wang et al., 2015).

Taking into consideration the link between ruminators' excessive smartphone use and their compensatory desires (Wang et al., 2015; Wolniewicz et al., 2018), it is plausible that rumination indirectly influences smartphone use via coping functions that are attained through smartphone use. In line with this notion, the compensatory internet use model holds that individuals go online because of specific motivations to alleviate negative feelings caused by stressors such as negative life events (for a review, see Kardefelt-Winther, 2014). Although coping through smartphone use has yet to be widely examined, studies on online (i.e., internet) coping highlight three primary types: mental disengagement, problem-focused coping, and socioemotional coping (for a review, see van Ingen et al., 2016). Given that smartphone use is tightly interwoven with internet consumption (Duke & Montag, 2017; Kwon et al., 2013) and smartphone devices provide extensive functionalities such as virtual friends, personal assistants, entertainment, and information (Fullwood et al., 2017), it is plausible that smartphones can be used to support useful coping strategies.

Not surprisingly, given that smartphones have been found to compensate for individuals' needs for escapism or social connectedness (Wang et al., 2015; Wolniewicz et al., 2018), the compensatory internet use model has received empirical support in explaining ruminators' excessive smartphone use (Elhai, Tiamiyu, & Weeks, 2018; Wang et al., 2015; Wolniewicz et al., 2018). Specifically, ruminators may resort to playing games or visiting websites on smartphones to mentally disengage from their negative thoughts. Past studies have found that individuals' maladaptive smartphone use is partly driven by mental disengagement (Wang et al., 2015). Similarly, given that smartphones can serve as a gateway for excessive information search—e.g., cyberchondria, which is a form of anxiety characterized by excessive online health research (McElroy & Shevlin, 2014)—ruminators may turn to their smartphones for problem-focused coping to alleviate their rumination by performing an extensive search for problem-related information (Nolen-Hoeksema et al., 2008). On the other hand, ruminators may turn to their smartphones for socioemotional coping to co-ruminate through extensive and repetitive discussions of personal problems within dyadic relationships (Davidson et al., 2014; Jose et al., 2012). Given smartphones' support of numerous social networking platforms, they can undoubtedly satisfy ruminators' incessant need to connect with others for co-rumination. In favor of this notion, previous studies have found that ruminators who co-ruminate are prone to engage in frequent text messaging on smartphones (Davila et al., 2012). Taken together, it is conceivable that ruminators manage their ruminative thoughts by using smartphones, which may play compensatory coping roles.

Despite the empirical importance of understanding specific coping functions via smartphone use, scant research has investigated them as potential mediators in the relation between rumination and smartphone use. Further, several methodological issues preclude firm conclusions about their relations. First, the lack of objective assessments of smartphone use (e.g., Elhai, Levine et al., 2018; Elhai & Contractor, 2018) impedes clear understanding of the pathway between rumination and smartphone use. Specifically, given that individuals often inaccurately recall their smartphone use on subjective assessments (e.g., self-report; Andrews et al., 2015; Boase & Ling, 2013), it is critical that we precisely quantify smartphone use.

Another methodological limitation is the dominant reliance on cross-sectional designs, which prevents observation of the relation between rumination and trajectories of smartphone use. Although a few studies employ longitudinal designs and objective assessments, they report a lack of significant changes in smartphone use over time, which suggests that smartphone use may be time-invariant (Elhai, Tiamiyu, Weeks et al., 2018; Rozgonjuk et al., 2018). However, these findings may be inconclusive for the following reasons. First, the period of assessment (e.g., 1 week) in previous studies may be too short to capture reliable changes in smartphone use (Elhai, Tiamiyu, Weeks et al., 2018; Rozgonjuk et al., 2018). Second, a *linear* growth curve model may not be suitable to capture changes in smartphone use over time (Rozgonjuk et al., 2018), because it assumes a uniform increase or decrease in smartphone use; this is theoretically and empirically less plausible (Wilcockson et al., 2018). Specifically, uses and gratification theory (Blumler, 1979) suggests that adaptive smartphone use entails inconsistent changes in use due to varying needs and goals. Given this, the linear models employed in previous studies may not be sufficiently sensitive to capture participants' nonlinear patterns (e.g., quadratic or piecewise; Duncan & Duncan, 2009) of smartphone use over time.

In view of these methodological constraints, we used a latent growth curve approach and fitted either linear or nonlinear latent growth curve models to smartphone use data to examine potential changes in smartphone use, as assessed both subjectively and objectively, over an extended period of 5 weeks. Further, given that no study, to our best knowledge, has examined smartphone coping, we examined our primary hypothesis that smartphone coping functions would mediate the relation between rumination and changes in smartphone use. To achieve our goals, we used a structural equation model and examined the parallel mediational relations between rumination and smartphone use via different forms of smartphone coping.

2. Method

2.1 Participants and procedure

We recruited participants from a local university in Singapore. Those who consented to the collection of screen time data from their personal smartphones participated in the study in exchange for either course credit or monetary compensation ($30). Given that piecewise latent growth curves are more complex than linear or quadratic growth curves, we calculated our minimum sample size to ensure sufficient power to detect piecewise linear trajectories (Diallo & Morin, 2015). According to a Monte Carlo simulation, 200 participants are necessary to attain more than 80% power to detect moderate differences (i.e., 0.16) between the two piecewise slopes. With further consideration of the high attrition rate (up to 25%) in multi-time-point studies, we recruited 251 participants. Thirty-four dropped out during the study period, resulting in a sample size of 217 (mean age = 21.8 years; female = 74.1%).

Participants first attended a briefing regarding the use of specific screen time monitoring applications. Afterward, a weekly survey link was sent to participants over a period of 5 weeks, which required that they complete a series of questionnaires and provide screenshots of the specified applications within a stipulated time window (i.e., 6:00 p.m. –11:59 p.m. every Thursday). All procedures were approved by the university's institutional review board.

2.2 Measures

2.2.1 Rumination

Participants' ruminative thinking style was assessed weekly using the 15-item Ruminative Thinking Style Questionnaire (RTSQ; Tanner et al., 2013) for 5 weeks. The scale consisted of four subscales: (a) repetitive (four items; α = .949; e.g., "In the past 7 days, I find that my mind goes over things again and again"); (b) problem-focused (five items; α = .916; e.g., "In the past 7 days, even if I think about a problem for hours, I still have a hard time coming to a clear understanding"); (c) counterfactual (four items; α = .909; e.g., "In the past 7 days, I find myself daydreaming about things I wish I had done"); and (d) anticipatory rumination (two items; α = .854; e.g., "In the past 7 days, if I have an important event coming up, I can't stop thinking about it"). Participants were asked to rate their agreement with each statement on a 7-point scale (1 = *strongly disagree*; 7 = *strongly agree*). Given that an individual's ruminative thinking style is theorized to be relatively stable (Brinker & Dozois, 2009; see Appendix Table A1 for test-retest reliability), participants' score for each scale item was averaged over five time points. Higher scores indicated greater ruminative tendencies.

2.2.2 Smartphone use

2.2.2.1 Objective smartphone use

Participants provided weekly screenshots of their screen time as monitored by specific applications on their smartphones for 5 weeks. iPhone users used the default *Screen Time* monitoring app (Apple Inc., 2019), and Android smartphone users used a free screen time monitoring application called *Screen Time—Restrain Yourself & Parental Control* (Iridium Dust

Limited, 2020). Both screen time monitoring applications captured the total amount of screen time in the previous week. Total screen time captured was divided by the number of days of screen time to derive the average daily objective smartphone use (in hours) for each participant at each time point.

2.2.2.2 Self-reported smartphone use

The self-reported smartphone use scale was adapted from Rosen et al. (2013). In each weekly survey, participants reported the estimated amount of time they spent on 14 different smartphone activities (e.g., text/instant messaging, email, social networking sites) on a 9-point scale (0 = *not at all*; 9 = *more than 10 hours per day*). The number of hours across the activities were summed at each time point.

2.2.3 Smartphone coping

Participants reported their weekly smartphone coping through an adapted 14-item online coping scale over 5 weeks (van Ingen et al., 2016). The scale consisted of three subscales: (a) mental disengagement (two items; α = .882; e.g., "In the past 7 days, I turned to my smartphone to take my mind off things"); (b) problem-focused coping (six items; α = .952; e.g., "In the past 7 days, with the aid of my smartphone, I thought hard about what steps to take"); and (c) socioemotional coping (six items; α = .930; "In the past 7 days, I received comfort and understanding from someone through the use of my smartphone"). Participants responded using a 5-point scale (1 = *never*; 5 = *always*). Higher scores on a subscale indicate greater tendencies to use one's smartphone for a specific form of coping.

2.2.4 Covariates

Participants provided their age, gender, and monthly household income, all of which have been shown to influence smartphone use (Silver, 2019; van Deursen et al., 2015). Given the close relations between rumination, depression, and smartphone use (Elhai, Tiamiyu, & Weeks, 2018; Nolen-Hoeksema et al., 2008), we assessed and controlled for depressive symptomology by adapting the 10-item short form of the Center for Epidemiological Studies Depression Scale (CES-D-10; $\alpha = .808$; Andresen et al., 1994). Participants rated the frequency with which they experienced specific symptoms in the past week on a 4-point scale (1 = *rarely or none of the time, less than 1 day*; 4 = *most of or all the time, 5–7 days*). Items were recoded and averaged such that higher scores indicate greater depressive symptomology.

3. Results

3.1 Analytic plan

All analyses were conducted using M*plus* 7.4 (Muthén & Muthén, 2015) with full information maximum likelihood estimation. First, we fitted various latent growth curves to the data on objective and subjective smartphone use and smartphone coping to examine whether these constructs change over time (Duncan & Duncan, 2009). In contrast, rumination (i.e., the focal predictor), which is known to be time-invariant, was modeled as a latent variable using confirmatory factor analysis. Afterward, we performed structural equation modeling to examine a mediational model in which the three forms of smartphone coping mediate, in parallel, the indirect effect of rumination on the latent growth curve of smartphone use.

To evaluate the model fit of individual models, the following criteria were adopted: root mean square error of approximation (RMSEA) values equal to or below .08 and .06 indicate acceptable and good fit, respectively; comparative fit indices (CFI) close to or greater than .95;

and standardized root mean squared residual (SRMR) values equal to or below .08 (Hooper et al., 2008; Hu & Bentler, 1999). Because it was not appropriate to use the Chi-square difference test to compare the fit of alternative latent growth models that are not formally nested within each other, information criteria—such as the Akaike information criterion (AIC) and sample-size adjusted Bayes information criterion (BIC) statistics—were used to identify the best-fitting model (Flora, 2008). Smaller AIC and BIC values indicate that a model is more likely to be the true model (Bollen & Curran, 2006).

3.2 Descriptive analyses

Descriptive statistics showed that daily objective smartphone use was positively, but only moderately, correlated with self-reported smartphone use, $r = .29$, $p < .001$ ($n = 235$), which suggests that these two measures do not mirror each other closely. Further, given that the two screen time monitoring applications (i.e., iOS versus Android applications) were similar but not identical, we ran a simple post hoc multivariate ANOVA to examine group differences in objective smartphone use across all time points, and none were significant ($F_{T1}(1, 237) = 2.77$, $p_{T1} = .098$; $F_{T2}(1, 237) = 2.29$, $p_{T2} = .131$; $F_{T3}(1, 237) = 0.0\ 8$, $p_{T3} = .780$; $F_{T4}(1, 237) = 1.35$, $p_{T4} = .247$; $F_{T5}(1, 237) = 0.02$, $p_{T1} = .90$). Thus, we collapsed the two groups of users into one for subsequent analyses.

Table 1

Model Fit Indices and Slope Statistics for Latent Growth Curve Models

	Fit indices							Slope mean		Slope variance	
	χ^2	*df*	RMSEA	CFI	SRMR	AIC	BIC[1]	*B*	*SE*	*B*	*SE*
Objective smartphone use											
Linear	23.09*	10	.074	.99	.044	3233	3236	0.097***	0.022	0.039**	0.012
Quadratic	13.46*	6	.073	.99	.042	3232	3236	0.041**	0.014	0.041	0.120
Piecewise[2]	10.35	6	.055	1.00	.042	3228	3232	*0.011*	*0.034*	*0.054*	*0.049*
								0.207***	0.041	0.111	0.062
Self-reported smartphone use											
Linear	61.63***	10	.151	.95	.085	6714	6717	-0.646***	0.124	1.99***	0.335
Quadratic	20.795**	6	.104	.98	.049	6682	6685	0.250**	0.072	0.784***	0.163
Piecewise[2]	18.27**	6	.095	.99	.046	6679	6683	*-1.373****	*0.215*	*7.721****	*1.512*
								-0.185	0.177	7.226***	1.409
Smartphone coping											
Mental disengagement											
Linear	14.33	10	.043	.99	.047	2638	2640	-0.007	0.016	0.019**	0.007
Quadratic	5.51	6	.000	1.00	.031	2636	2641	0.013	0.010	-0.011**	0.004
Piecewise[2]	7.40	6	.032	1.00	.030	2638	2642	*-0.036*	*0.030*	*-0.039*	*0.036*
								0.019	0.026	-0.047	0.031
Socioemotional coping											
Linear	12.85	10	.035	1.00	.026	2553	2555	0.007	0.016	0.023***	0.006
Quadratic	8.28	6	.021	1.00	.035	2556	2559	0.004	0.011	0.006	0.004
Piecewise[2]	7.36	6	.031	1.00	.034	2555	2559	*-0.011*	*0.029*	*0.040*	*0.029*
								0.017	0.029	0.085***	0.029
Problem-focused coping											
Linear	16.56	10	.054	.99	.032	2281	2284	-0.004	0.012	0.010**	0.004
Quadratic	12.40	6	.068	.99	.033	2285	2289	0.004	0.009	0.002	0.002
Piecewise[2]	11.56	6	.064	.99	.033	2284	2288	*-0.023*	*0.025*	*0.042**	*0.019*
								0.012	0.021	0.017	0.019

Note. * $p < .05$; ** $p < .01$; *** $p < .001$.

[1] BIC was adjusted for sample size.

[2] Since there are two slopes (i.e., 1st slope and 2nd slope) in piecewise growth curve models, statistics for the 1st slope are in italics.

3.3 Latent growth curve models

Little's (1988) missing data analysis showed that data are missing completely at random, $\chi^2(515) = 522.11$, $p = .405$. We estimated latent intercepts and slopes for smartphone use and smartphone coping. For the linear model, we estimated the linear slope by fixing equidistant time scores (i.e., 1-week intervals) across the five time points. For the quadratic and piecewise models, we estimated a quadratic slope and two piecewise linear slopes, respectively (Muthén and Muthén, 2008).

3.3.1 Smartphone use

To examine potential changes in objective smartphone use across 5 weeks, we tested various unadjusted growth models (without covariates). Average daily screen time (in hours) at each time point served as the indicators. The linear growth model showed good model fit, with a significant slope mean ($B = 0.097$, $p < .001$; see Table 1). These results signify that there is a significant linear increase in smartphone use over the 5 weeks. Next, we fitted a quadratic growth model and found good model fit, with a significant quadratic slope mean ($B = 0.041$, $p = .003$; see Table 1).

Lastly, we fitted a piecewise growth model to the data, which allowed two linear slopes to be modeled over a given period with a specified turning point (Flora, 2008). We specified time point 3 (herein called "T3") as the turning point, because during the study period, midterm examinations were cancelled at T3 due to the outbreak of COVID-19 in the country (Abdullah & Salamat, 2020; Yong, 2020). Such an extraordinary change should inevitably affect our participants' academic stress, which in turn influences their smartphone use (Chiu, 2014; Samaha & Hawi, 2016). More details about our study's context and justification for the turning point are presented in the discussion section. Further, our inspection of the modification indices for the linear growth curve also supported the specification of T3 as the turning point (Kwok et al., 2010). The piecewise growth model demonstrated good fit (see Table 1), with a nonsignificant slope between T1 and T3 (i.e., slope1; $B_{s1} = 0.011$, $p_{s1} = .738$) and a significant slope between T3 and T5 (i.e., slope2; $B_{s2} = 0.207$, $p_{s2} < .001$). These results demonstrate that participants' smartphone use increased significantly after T3, which is congruent with our expected consequences of exam cancellation. According to the AIC and sample-size adjusted BIC (see Table 1), the piecewise model was closest to the true model (Bollen & Curran, 2006); thus, we retained it for further analyses. For all tested models, the factor loadings of the indicators were significant (*p*s < .001).

Similar analyses were conducted with respect to self-reported smartphone use. The indicators were daily screen time (in hours), which was summed across 14 activities at each time point. The factor loadings of the indicators for all models were significant (*p*s < .001). However, the model fit indices of all tested latent growth curve models were unacceptable (see Table 1), which means that the models have errors, are not reliable, and do not represent the data. Thus, we did not consider self-reported smartphone use in our subsequent structural equation modeling.

3.3.2 Smartphone coping

We fitted latent growth models to estimate changes in each form of smartphone coping—mental disengagement, problem-focused coping, and socioemotional coping—across 5 weeks. Indicators for the respective models were the averaged subscale scores at each time point. The factor loadings of all indicators were significant (*p*s < .001). For all smartphone coping functions, although the model fit indices of the linear, quadratic, and piecewise models were acceptable, none of the models showed significant means for the slope growth factors (see Table 1), which suggests that smartphone coping showed little change over the 5 weeks. Therefore, we modeled the three forms of smartphone coping as latent factors instead of latent growth factors.

Table 2

Model Fit Indices for Measurement and Structural Models

	χ^2	*df*	RMSEA	CFI	SRMR
Measurement models					
Rumination (one-factor)	2.21	1	.073	1.00	.007
Smartphone coping (three-factor model with modifications)	99.41***	43	.077	.98	.040
Full measurement model	283.01***	163	.055	.98	.042
Structural models					
Rumination → smartphone use[1] (unadjusted[2])	31.58	24	.037	1.00	.036
Rumination → smartphone use[1] (adjusted[2])	138.65***	48	.091	.95	.093
Rumination → coping[3] → smartphone use[1] (unadjusted[2])	436.77***	166	.082	.94	.144
Rumination → coping[3] → smartphone use[1] (adjusted[2])	624.34***	238	.084	.92	.140

Note. * $p < .05$; ** $p < .01$; *** $p < .001$.
[1] Smartphone use is based on the objective measure.
[2] Unadjusted models did not include the covariates of age, gender, monthly household income, and depressive symptomology, and adjusted models included these covariates.
[3] Coping refers to smartphone coping.

3.4 Measurement models

3.4.1 Rumination

In line with Tanner et al. (2013), we fitted a four-factor model to the data with the scale item's averaged scores over five time points as indicators (see Figure A1 in the Appendix). However, since the model fit was unacceptable, $\chi^2(83) = 396.12$, RMSEA = .132, CFI = .91, SRMR = .051, we computed the average subscale score over five time points and fitted a one-factor model with the four subscale scores as indicators (Brinker & Dozois, 2009). The model fit was acceptable, $\chi^2(1) = 2.21$, RMSEA = .073, CFI = 1.00, SRMR = .007. Thus, the one-factor model for rumination was used in further analyses.

3.4.2 Smartphone coping

Since the construct of smartphone coping did not change over time, we conceptualized it as a latent factor instead of a latent growth factor. As suggested by van

Ingen et al. (2016), we fitted a three-factor model for smartphone coping. The scale item's averaged scores across five time points were the indicators (see Appendix Figure A2). However, the model fit was unacceptable, $\chi^2(71) = 450.50$, RMSEA = .156, CFI = .90, SRMR = .134. Hence, we fitted the model again in line with modification indices. Adjusting for the cross-loading indicators and correlating the residuals of some scale items that were similarly worded greatly improved the model fit (van Ingen et al., 2016). The measurement model displayed acceptable fit after making these adjustments, $\chi^2(43) = 99.41$, RMSEA = .077, CFI = .98, SRMR = .040. The factor loadings of all indicators were significant (*p*s < .001). Thus, we retained the three-factor model for smartphone coping.

3.4.3 Full measurement model

The full measurement model included the single-factor rumination, three-factor smartphone coping, and piecewise latent growth curve of objective smartphone use. The full measurement model had a good fit, $\chi^2(163) = 283.01$, RMSEA = .055, CFI =.98, SRMR = .042. The factor loadings of all indicators were significant (*p*s < .001).

3.5 Structural models for testing mediation effects

To examine whether smartphone coping mediates the relation between rumination and objective smartphone use, we performed a mediational structural equation analysis that included all three forms of coping—mental disengagement, problem-focused coping, and socioemotional coping—to understand the unique effect of each coping factor while controlling for their shared variance. We found that mental disengagement was the only significant mediator that accounted for the relation between rumination and initial levels (intercept) of smartphone use ($\beta_{int} = 0.159$, $SE_{int} = 0.064$, $p_{int} = .013$). However, mental disengagement did not mediate the relations between rumination and changes in smartphone use (slopes; $\beta_{s1} = 0.257$, $SE_{s1} = 0.138$, $p_{s1} = .063$; $\beta_{s2} = 0.048$, $SE_{s2} = 0.111$, $p_{s2} = .667$). Indirect effects pertaining to problem-focused coping ($\beta_{int} = -0.008$, $SE_{int} = 0.064$, $p_{int} = .900$;

β_{s1} = -0.138, SE_{s1} = 0.134, p_{s1} = .304; β_{s2} = -0.072, SE_{s2} = 0.121, p_{s2} = .553) and socioemotional coping (β_{int} = 0.008, SE_{int} = 0.042, p_{int} = .840; β_{s1} = -0.089, SE_{s1} = 0.087, p_{s1} = .306; β_{s2} = 0.036, SE_{s2} = 0.078, p_{s2} = .645) were not significant for all growth factors of smartphone use.

Next, we examined a similar mediational structural equation model by including the covariates (i.e., adjusted model; see Figure 1). The results did not differ much from those of the unadjusted model. Mental disengagement was the only significant mediator between rumination and initial levels of smartphone use (β_{int} = 0.160, SE_{int} = 0.064, p_{int} = .013). Rumination positively predicted mental disengagement (β = 0.540; SE = 0.060, p < .001), which, in turn, positively predicted only initial levels of smartphone use (β_{int} = 0.296; SE_{int} = 0.112, p_{int} = .008). Since the direct effect of rumination on initial levels of smartphone use was not significant (β_{int} = -0.070, SE_{int} = 0.103, p_{int} = .498), this implies that mental disengagement fully mediated the relation between rumination and initial levels of smartphone use. In contrast, mental disengagement did not mediate the relation between rumination and changes in smartphone use (β_{s1} = 0.253, SE_{s1} = 0.141, p_{s1} = .072; β_{s2} = 0.074, SE_{s2} = 0.102, p_{s2} = .465). That is, the predictive effect of rumination on smartphone use, via mental disengagement, was apparent only for initial levels of smartphone use.

In the adjusted model, all indirect effects pertaining to problem-focused coping (β_{int} = -0.008, SE_{int} = 0.062, p_{int} = .900; β_{s1} = -0.155, SE_{s1} = 0.136, p_{s1} = .252; β_{s2} = -0.055, SE_{s2} = 0.108, p_{s2} = .612) and socioemotional coping (β_{int} = 0.017, SE_{int} = 0.042, p_{int} = .694; β_{s1} = -0.084, SE_{s1} = 0.089, p_{s1} = .346; β_{s2} = 0.028, SE_{s2} = 0.072, p_{s2} = .698) were not significant for all growth factors of smartphone use. Although rumination positively predicted problem-focused and socioemotional coping, both forms of coping did not significantly predict any growth factors of smartphone use (see Figure 1). These results imply that individuals with higher rumination resort to more problem-focused and socioemotional coping through their smartphones, but these forms of coping do not influence the length of their smartphone use.

Notably, the direct effect of rumination on later-phase trajectories (i.e., slope2) of smartphone use between T3 and T5 was significant (β_{s2} = 0.418, SE_{s2} = 0.198, p_{s2} = .035). In view of the null indirect effect of rumination on changes in smartphone use between T3 and T5, these results suggest that ruminating individuals tend to experience greater increments in smartphone use between T3 and T5, but this relation is not mediated by any specific forms of smartphone coping.

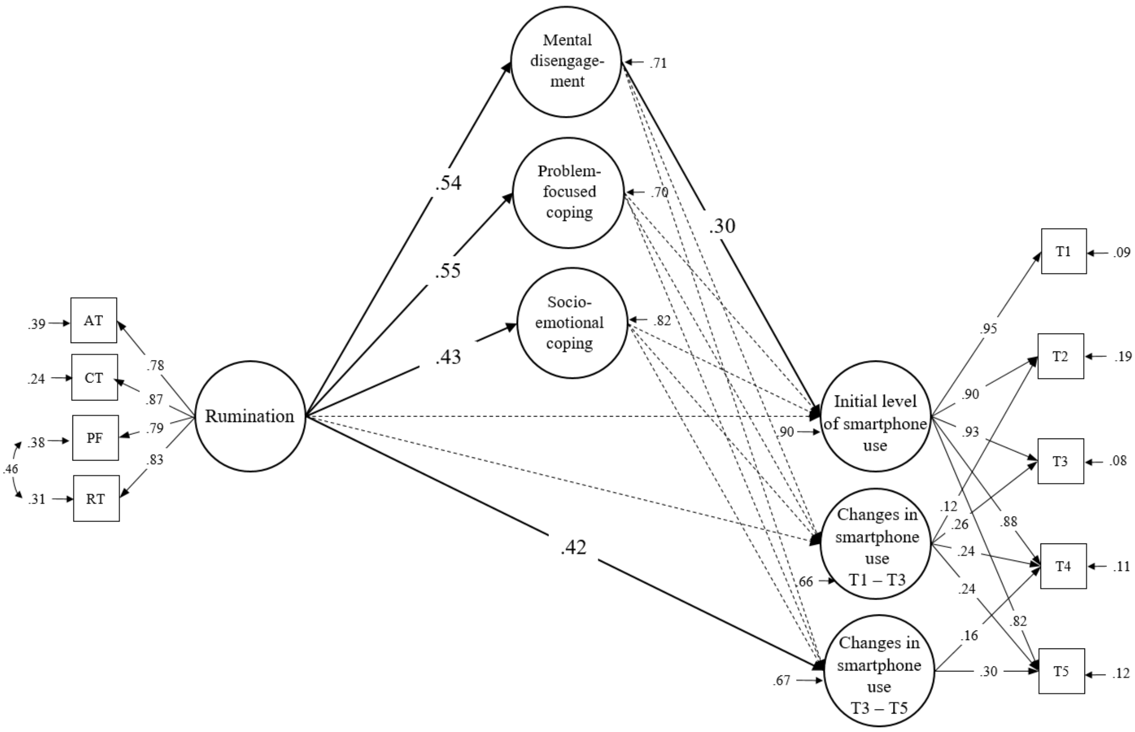

Figure 1. Adjusted structural model of rumination, smartphone coping, and objective smartphone use. Circles represent latent (growth) factors. Squares represent indicators (manifest variables); AT – RT = averaged subscale scores of anticipatory (AT), counterfactual (CT), problem-focused (PF), and repetitive (RT) rumination over five time points; T1 – T5 = average daily objective smartphone use (in hours) at time points 1 to 5. Indicators of the mediators (three-factor smartphone coping) and covariates (age, gender,

monthly household income, depressive symptomology) are not depicted for brevity. Values on the longer, single-headed arrows signify path coefficients. Values for the smaller, single-headed arrows represent residual variances. Values for the curved, double-headed arrows indicate correlations between residual variances. All coefficients shown are standardized and attained statistical significance at the .05 level. Dotted lines indicate nonsignificant pathways.

4. Discussion

Using rigorous latent growth curve and structural equation modeling analyses, we obtained several notable findings. First, building on the theoretical account of the internet compensatory use model (Kardefelt-Winther, 2014), our results provide first evidence that elucidates the mechanism that underlies the relation between rumination and smartphone use over time. We found that individuals' ruminative tendencies indirectly influenced their initial levels of smartphone use, but not their changes in smartphone use over time, via smartphone coping. More importantly, mental disengagement, but neither problem-focused nor socioemotional coping, significantly accounted for the mediational relation between rumination and initial levels of smartphone use. These results suggest that using smartphones for mental disengagement provides a uniquely rewarding experience for ruminators by alleviating negative thoughts about stressors. Consequently, this rewarding experience via mental disengagement becomes a positive reinforcement that drives ruminators' smartphone overuse (Wang et al., 2015). In contrast, problem-focused and socioemotional coping do not provide similarly rewarding experiences, because they may instead escalate rumination by yielding more problem-related information or facilitating co-rumination, respectively. Since these forms of coping may not fulfill the compensatory purpose of reducing the negative feelings rumination entails, their use may be less satisfying over a lengthy period. These findings provide further evidence that the internet compensatory use model is applicable to smartphone use (Kardefelt-Winther, 2014; Wang et al., 2015; Wolniewicz et al., 2018).

Future studies should, therefore, consider smartphone coping as an important construct in studying smartphone use.

Our second notable finding is that rumination positively predicted increments in participants' objective smartphone use over time, which is consistent with previous research that suggests a positive relation between rumination and smartphone use (e.g., Elhai & Contractor, 2018). Further, we obtained two noteworthy findings: (a) participants' objective smartphone use significantly increased only between T3 and T5, and (b) smartphone coping did not mediate the relations between rumination and changes (i.e., slope) in smartphone use between T3 and T5. These findings should be interpreted based on the context in which the study took place. When the study was conducted, COVID-19 was spreading rapidly within local communities in Singapore (Abdullah & Salamat, 2020; Yong, 2020). Due to increasing uncertainty, fear, and anxiety, all midterm examinations were cancelled in the university, which caused a sudden academic disruption at T3; although there were other events—such as temporary panic purchases of groceries and hygiene products, especially by middle-aged and older adults—we assume that these events were less impactful on our participants, who were college students. Importantly, the sudden academic interruption could have engendered greater changes in ruminators' smartphone use for either coping (e.g., increased smartphone use for problem-focused information search) or non-coping reasons (e.g., increased smartphone use for academic communication and collaborations due to increased weight assigned to projects). The academic disruption, therefore, provides strong justification for specifying the turning point (i.e., T3) in our piecewise latent growth curve model. Further, this notion is support by our findings of the significant predictive (direct) effect of rumination on increases in smartphone use between T3 and T5, but a null mediation effect of smartphone coping on the relation between rumination and changes in smartphone use during the same period. Future studies should, therefore, clarify this issue by examining specific contextual life events (e.g., exam cancellation or COVID-19) or factors (e.g., heightened anxiety or stress) that influence ruminators' reliance on smartphone coping.

The third notable finding of our study pertains to the significant changes in objective smartphone use over a 5-week period via three latent growth models (i.e., linear, quadratic, and piecewise). These findings are contrary to previous studies' finding of nonsignificant changes in smartphone use (Elhai, Tiamiyu, Weeks et al., 2018; Rozgonjuk et al., 2018) and the prevailing notion that smartphone use is consistent and largely invariant (Wilcockson et al., 2018). Our findings attest to the importance of considering extended longitudinal observations (i.e., longer than 1 week) and nonlinear or piecewise growth models for objective smartphone use. Further, our finding that smartphone coping remained relatively unchanged over time suggests that ruminators' use of smartphones for coping may be habitual. Given ruminators' weaker coping abilities (Nolen-Hoeksema et al., 2008), it is conceivable that they form a habitual and addictive reliance on smartphones for mental disengagement, which is manifested as heavier smartphone use.

Lastly, our study also highlights the validity of using an objective measure of smartphone use over a self-reported measure (Boase & Ling, 2013). The modest correlation between these measurements shows that they do not closely mirror each other. These results indicate that objective measures are more accurate than self-reported ones; therefore, future studies should consider using objective measures to achieve greater measurement validity.

Our study is not without limitations. First, the use of daily screen time for objective smartphone use does not differentiate smartphone use on weekend days versus weekdays. Given that smartphone use on those respective days differs (Filiposka & Mishkovski, 2013) and may perpetuate different outcomes (Hartanto et al., 2018), it is essential that we understand whether rumination differentially affects smartphone use on weekdays versus weekends. Second, the self-reported measure of smartphone use may not be comparable to the objective measure, because the former asks participants to provide independent estimates of their smartphone use for 14 activities instead of a single overall estimate of the amount of time they spent on their smartphones daily. Although this was done to provide a useful reference so that participants could recall their smartphone usage better, it could have unnecessarily inflated overall estimates due to multitasking. Third, our study focused on college students, who tend to use smartphones heavily for productivity or entertainment purposes. Thus, our results may not be generalizable to other populations, such as middle-aged or older adults, who may differ in their motivations for and patterns of smartphone use (Silver, 2019). Finally, given that our participants were aware that their smartphone use was being actively monitored during the study period, potential demand characteristics could affect participants' smartphone use in general. Nevertheless, given that our choice of monitoring applications is less intrusive than those with warning notifications about excessive smartphone use—which in any case did not affect participants' smartphone use patterns (Loid et al., 2020)—we believe that the potential impact of demand characteristics may be minimal.

Our study contributes to the literature and our practical understanding of smartphone use in several notable ways. First, our findings are novel because they elucidate the specific pathway through which rumination impacts objective smartphone use. These findings provide new practical insights into the critical role of one's motivation for smartphone use (i.e., using smartphones for coping) in triggering smartphone overuse. Specifically, smartphones can be used to satisfy such motivational or coping needs, and thereby entail a significant increase in smartphone use. Therefore, on a practical note, counselors and policymakers should consider the motivations underlying excessive smartphone use in designing interventions for ruminators to overcome possible maladaptive or addictive smartphone-use habits. Importantly, our findings demonstrate that the predictive power of rumination for smartphone use via specific smartphone coping functions (i.e., mental disengagement) can be more accurately estimated through longitudinal smartphone use assessment. Second, by using rigorous latent growth curve modeling, our study demonstrates that individuals' objective smartphone use does vary over time, especially when stressful life events arise; this argues against the prevailing notion. Third, this study contrasts different measurements of smartphone use, which highlights the need to use a more precise and valid objective method in future studies. Together, by highlighting the need to consider the motivations that underlie smartphone use, our findings imply potential ways ruminators choose to regulate their excessive smartphone use to avoid adverse outcomes, which may have a crucial impact on their subjective well-being.

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6. Appendix

Table A1

Test-retest Reliability of Measures

	T2	T3	T4	T5
Repetitive rumination				
T1	.63	.50	.59	.61
T2		.59	.59	.54
T3			.60	.57
T4				.70
Problem-focused rumination				
T1	.62	.50	.56	.61
T2		.54	.63	.59
T3			.61	.60
T4				.74
Anticipatory rumination				
T1	.52	.41	.44	.48
T2		.62	.53	.56
T3			.51	.60
T4				.59
Counterfactual rumination				
T1	.70	.65	.66	.68
T2		.71	.71	.73
T3			.73	.71
T4				.75
Objective smartphone use				
T1	.71	.50	.50	.52
T2		.68	.62	.54
T3			.70	.58
T4				.74
Self-reported smartphone use				
T1	.76	.68	.60	.61
T2		.80	.74	.69
T3			.81	.78
T4				.85
Smartphone coping				
Mental disengagement				
T1	.42	.49	.51	.41
T2		.45	.50	.52
T3			.57	.64
T4				.64
Problem-focused coping				
T1	.60	.59	.56	.56
T2		.68	.58	.61
T3			.66	.69
T4				.75
Socioemotional coping				
T1	.60	.59	.56	.56
T2		.66	.58	.61
T3			.66	.69
T4				.75

Note. T1 – T5 = Timepoint 1 – 5. Statistics computed using Pearson's correlation coefficient. All statistics are significant at $p < .001$ level.

Table A2

Descriptive Statistics of All Variables and Covariates

	M	*SD*	Min	Max	Skew-ness	Kurtosis	Reliability[1] T1	T2	T3	T4	T5
Focal predictor – Rumination											
Repetitive	4.58	1.11	1.75	7.00	-0.27	-0.18	.85	.86	.87	.91	.89
Problem-focused	3.83	1.06	1.36	6.48	0.08	-0.42	.83	.83	.86	.87	.88
Counterfactual	4.34	1.21	1.10	6.90	-0.22	-0.29	.81	.85	.80	.84	.86
Anticipatory	4.37	1.06	1.30	6.70	-0.32	-0.26	.53	.72	.69	.70	.73
Mediators – Smartphone coping											
Mental disengagement	3.02	0.83	1.00	5.00	-0.16	-0.61	.80	.82	.80	.80	.80
Problem-focused	2.51	0.85	1.10	4.67	0.28	-0.85	.88	.89	.90	.90	.93
Socioemotional	2.76	0.87	1.00	5.00	-0.08	-0.84	.86	.87	.89	.89	.90
Dependent variable – Smartphone use (daily average in hours)											
Objective use T1	5.33	1.95	1.24	11.43	0.35	0.01	-	-	-	-	-
Objective use T2	5.37	2.18	0.94	12.82	0.58	0.19	-	-	-	-	-
Objective use T3	5.36	2.03	1.23	10.83	0.37	-0.26	-	-	-	-	-
Objective use T4	5.53	2.08	1.07	13.92	0.39	0.66	-	-	-	-	-
Objective use T5	5.65	2.30	1.09	12.43	0.49	-0.03	-	-	-	-	-
Self-reported use T1[2]	17.37	8.19	3.00	45.50	1.02	0.94	-	-	-	-	-
Self-reported use T2	15.85	8.13	3.50	55.50	1.56	3.72	-	-	-	-	-
Self-reported use T3	14.53	7.25	3.00	44.50	1.26	1.83	-	-	-	-	-
Self-reported use T4	14.63	8.93	3.50	54.00	1.84	3.75	-	-	-	-	-
Self-reported use T5	14.11	7.75	3.00	47.00	1.51	2.76	-	-	-	-	-
Covariates											
Depressive symptomology	2.12	0.44	1.00	4.00	0.68	0.92	.81	-	-	-	-
Age	21.78	1.75	18.00	27.00	0.17	-0.17	-	-	-	-	-
Gender[3]	1.74	-	-	-	-1.11	-0.78	-	-	-	-	-
Monthly household income[4]	4.16	2.35	1.00	9.00	0.70	-0.43	-	-	-	-	-

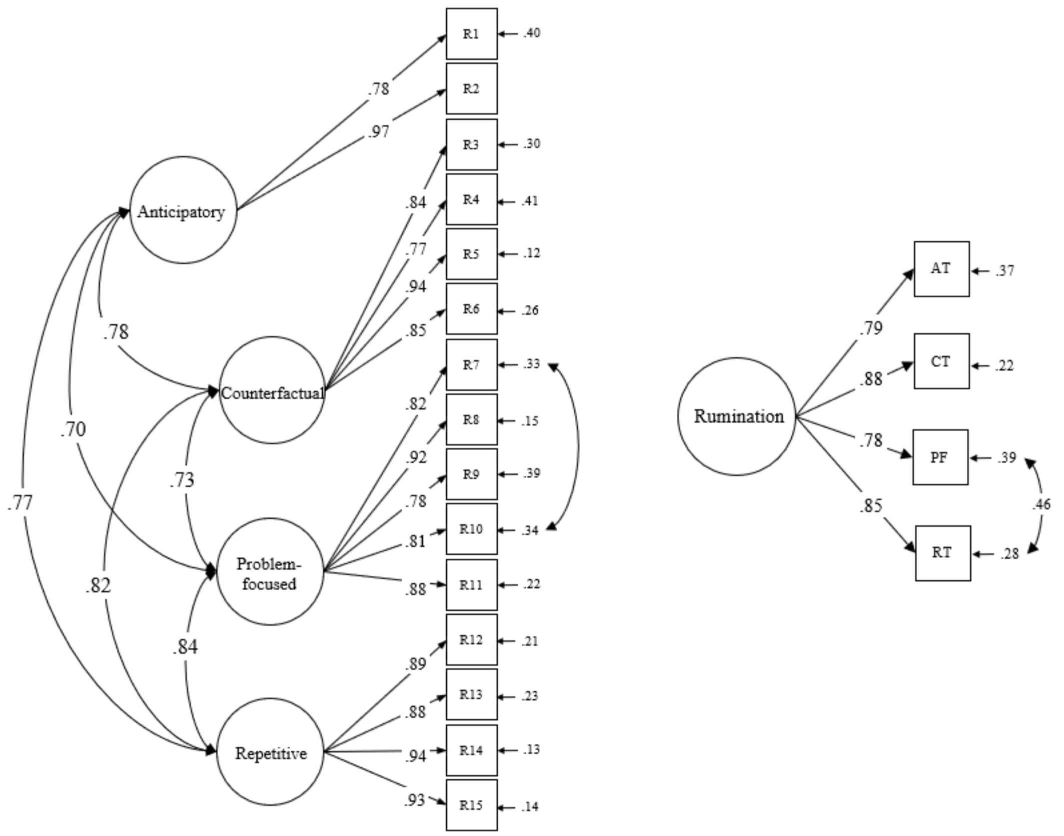
Note. [1] Reliability estimates were calculated using Cronbach's alpha.
[2] One participant's self-reported smartphone use was removed because it was identified as an outlier (2 – 3 times greater than other individuals' smartphone use).
[3] 1 = *Male*; 2 = *Female*.
[4] 1 = *Less than $2,500*, 2 = *$2,500 – $5,000*, 3 = *$5,000 - $7,999*, 4 = *$7,500 - $9,999*, 5 = *$10,000 - $12,499*, 6 = *$12,500 - $14,999*, 7 = *$15,000 - $17,499*, 8 = *$17,500 - $19,999*, 9 = *More than $20,000*

Table A3

Zero-order Correlations Between Variables

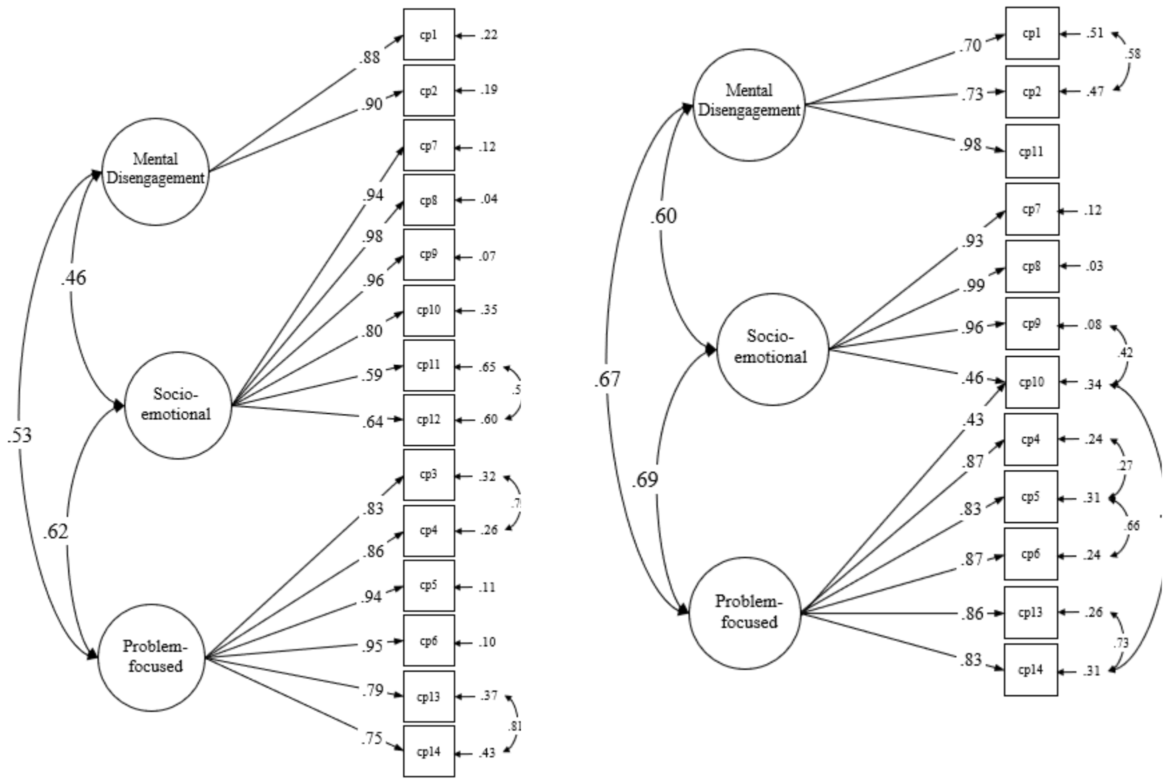
	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12.**
1. Objective smartphone use	-											
2. Self-reported smartphone use	**.29**	-										
3. Repetitive rumination	.09	**.21**	-									
4. Problem-focused rumination	.00	**.17**	**.82**	-								
5. Anticipatory rumination	.09	**.15**	**.66**	**.64**	-							
6. Counterfactual rumination	.12	**.20**	**.74**	**.68**	**.71**	-						
7. Mental disengagement	**.30**	**.34**	**.38**	**.36**	**.36**	**.33**	-					
8. Problem-focused coping	**.14**	**.27**	**.30**	**.41**	**.36**	**.41**	**.55**	-				
9. Socioemotional coping	**.19**	**.23**	**.31**	**.28**	**.28**	**.35**	**.50**	**.72**	-			
10. Age	-.10	-.08	**-.23**	**-.15**	-.08	**-.17**	-.11	-.08	**-.16**	-		
11. Gender	-.03	.12	**.16**	.05	-.01	.01	.05	.04	.13	**-.45**	-	
12. Monthly household income	.06	-.10	.09	.06	.09	.02	-.01	-.04	-.05	**-.21**	.09	-
13. Depressive symptomology	.02	**.20**	**.61**	**.64**	**.40**	**.43**	**.42**	**.36**	**.30**	**-.14**	.11	.01

Note. Bolded statistics are significant at $p < .05$ level.



Four-factor model of rumination **One-factor model of rumination**

Figure A1. Tested measurement models of rumination. Circles represent latent variables. Squares represent indicators (manifest variables; R1 – R15 = scale item's averaged scores over five time points; AT – RT = averaged score of anticipatory (AT), counterfactual (CT), problem-focused (PF), and repetitive (RT) rumination subscale over five time points). Nonsignificant residuals not depicted for brevity. Values on the longer, single-headed arrows signify loading values. Values for the smaller, single-headed arrows represent residual variances. Values on the curved, double-headed arrows indicate correlation coefficients. All coefficients shown are standardized and achieved statistical significance at the .05 level.



Three-factor model **Three-factor model with modifications**

Figure A2. Tested measurement models of smartphone coping. Circles represent latent variables. Squares represent indicators (manifest variables; cp1 – cp14 = scale item's averaged scores over five time points). Nonsignificant residuals not depicted for brevity. Values on the longer, single-headed arrows signify loading values. Values for the smaller, single-headed arrows represent residual variances. Values on the curved, double-headed arrows indicate correlation coefficients. All coefficients shown are standardized and achieved statistical significance at the .05 level.