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Differentiate to Regulate: Low Negative Emotion Differentiation is Associated with Ineffective Emotion Regulation Use, but not Strategy Selection

Elise K. Kalokerinos*

School of Psychology, The University of Newcastle

Yasemin Erbas*

Eva Ceulemans

Peter Kuppens

Faculty of Psychology and Educational Sciences, KU Leuven

*Joint First Authorship

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Correspondence should be addressed to Elise Kalokerinos, School of Psychology, University of Newcastle, Callaghan 2308, Australia. E-mail:elise.kalokerinos@newcastle.edu.au.

Abstract

Emotion differentiation, which involves experiencing and labeling emotions in a granular way, has been linked with well-being. It has been theorized that differentiating between emotions facilitates effective emotion regulation, but this link has yet to be comprehensively tested. In two experience-sampling studies, we examined how negative emotion differentiation was related to 1) emotion regulation strategy selection, and 2) the effectiveness of strategies in down-regulating negative emotion (Ns=200 and 101 participants; 34,660 and 6,282 measurements). Unexpectedly, we found few relationships between differentiation and the selection of putatively adaptive or maladaptive strategies. Instead, we found interactions between differentiation and strategies in predicting negative emotion. Among low differentiators, all strategies (Study 1) and 4 of 6 strategies (Study 2) were more strongly associated with increased negative emotion than among high differentiators. This suggests that low differentiation may hinder successful emotion regulation, supporting the idea that effective regulation may underlie differentiation benefits.

Sometimes you feel awful, but you cannot put your finger on any particular feeling – you feel angry, sad, and anxious all at once. At these times, you are showing low emotion differentiation. Emotion differentiation, or emotional granularity, is the ability to experience and label emotions precisely (Kashdan, Barrett, & McKnight, 2015). Differentiating between negative emotions is associated with well-being, and it is argued that this is because differentiation facilitates emotion regulation (Kashdan et al., 2015). When you can pinpoint your feelings - not angry, not sad, but anxious - you can successfully tailor regulation. This idea is central to theory but has not yet been empirically verified. We test this idea in two experience-sampling studies, investigating the associations between differentiation and emotion regulation strategy selection and effectiveness.

Affect is generalized, rather than context-specific. This contrasts with discrete emotions, which deliver unique contextual information (Schwarz, 2010). This information may underlie the benefits of emotion differentiation, facilitating adaptive responding (Kashdan et al., 2015) and potentially enabling effective emotion regulation (Barrett & Gross, 2001). There are multiple ways in which discrete emotional information could assist in regulation. For example, discrete emotions provide information about emotional cause and context, directing regulation towards appropriate targets. The identification of discrete emotions could also assist in the selection of the most effective regulation strategies for those emotions, and help in specifying emotion goals.

There is some empirical evidence supporting the link between differentiation and regulation. First, low differentiation is associated with stronger links between some maladaptive coping strategies and undesirable outcomes, including alcohol consumption and negative emotion (Kashdan, Ferssizidis, Collins, & Muraven, 2010), rumination and self-injury (Zaki, Coifman, Rafaeli, Berenson, & Downey, 2013), and brooding and depressive symptoms (Starr, Hershenberg, Li, & Shaw, 2017). Second, differentiation is linked to improved behavior regulation, including reduced aggression following anger (Pond et al., 2012) and reduced impulsivity (Tomko et al., 2015).

These studies provide initial evidence for a link between differentiation and some specific strategies. However, theory suggests a deeper link, spanning multiple strategies and processes. To our knowledge, only one study tests this deeper link. Barrett, Gross, Christensen, and Benvenuto (2001) asked 53 people to retrospectively report how much they used nine regulation strategies over the previous two weeks, and averaged these strategies together as an index of regulation. For the next two weeks, participants reported emotion during their most negative daily experience, which was used for indices of emotion differentiation and intensity. Greater negative (but not positive) differentiation was associated with stronger regulation, particularly at high emotional intensity.

This study suggests that differentiation is associated with increased regulation, but is limited in two respects. First, this study averaged all regulation strategies together, but strategies are differentially associated with well-being (Webb, Miles, & Sheeran, 2012). Thus, a strategy-specific approach is necessary. Second, this study does not investigate how effectively regulation shapes subsequent emotional outcomes. Given theory is centered around *effective* regulation, rather than *increased* regulation, such a test is crucial.

Here, we examine how negative emotion differentiation relates to both emotion regulation strategy selection and effectiveness. We focus specifically on negative differentiation since it has been more consistently linked with well-being than positive differentiation (Kashdan et al., 2015). We take a strategy-specific approach, assessing three strategies generally effective at reducing negative emotion (reappraisal, acceptance, distraction), two strategies generally ineffective at reducing negative emotion (rumination, suppression), and social sharing.

We tested two sets of hypotheses. First, we examined whether differentiation was linked to *strategy selection*, operationalized as the degree to which each strategy was used. Rumination and suppression are negatively associated with well-being, and often seen as maladaptive (Gross & John, 2003; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). In contrast, reappraisal and acceptance are positively associated with well-being, and often seen as adaptive (Ford, Lam, John, & Mauss, 2018; Gross & John, 2003). We hypothesized that differentiation would be positively associated with reappraisal and acceptance, and negatively associated with suppression and rumination (*Hypothesis 1)*.

Second, we examined whether differentiation was linked to *strategy effectiveness*, operationalized as the association between each strategy and subsequent negative emotion. Negative emotion reduction is only one component of effective regulation, but is our focus because it is the most common regulation goal in daily life (Riediger, Schmiedek, Wagner, & Lindenberger, 2009). We hypothesized that differentiation would moderate the relationship between strategies and negative emotion (*Hypothesis 2)*. Among low differentiators, we hypothesized that all strategies would be associated with increased negative emotion (*Hypothesis 2a)*, suggesting an inability to effectively implement any strategy. Among high differentiators, we hypothesized that reappraisal, acceptance, distraction, and sharing would be associated with decreased negative emotion (*Hypothesis 2b)*, and that the effects of suppression and rumination on negative emotion would be attenuated (*Hypothesis 2c)*. This would suggest effective use of putatively adaptive strategies and a buffer against maladaptive strategies.

We tested these hypotheses in two experience-sampling studies. The first consisted of three experience-sampling periods across a year, investigating these relationships in everyday life. The second was conducted during a real-life emotional event, investigating these relationships in an intense emotional period.

Study 1

Method

Data, code, and materials for both studies are available at osf.io/bmaf2. These data were part of a larger study which received approval from the KU Leuven ethics committee. We discuss only the measures analyzed for the current study. These data have been previously used to investigate other research questions: a list of other projects using these data is available on OSF.

Participants were Belgian students starting university at Wave 1. We aimed for 200 participants, allowing 80% power to detect small effects (with up to 25% attrition; r=.15, α=.05). We powered for small effects because these data were designed to test several diverse processes for other projects. Potential participants completed the CES-Depression Scale (Radloff, 1977). We used their scores to select a stratified sample, including participants across the well-being spectrum (for more detail, see Dejonckheere et al., 2018).

Our initial sample was 202 at Wave 1, 191 at Wave 2, and 178 at Wave 3. Participants were omitted from the final sample for two reasons. First, we omitted 2 participants who had poor compliance with the momentary surveys at Wave 1 (>50% of surveys completed), because of concerns around low quality responding (although results were identical with these participants included). One of these participants only completed Wave 1. One completed all waves, but showed poor compliance at every wave and was thus omitted from all time-points. No other participants showed poor compliance at Wave 2 or 3 (see below for more detail). This left us with 200 participants at Wave 1, 190 at Wave 2, and 177 at Wave 3.

Second, we excluded participants with emotion differentiation indices below 0 (2 at Wave 1, 5 at Wave 2; see the Measures section for more details). The participants excluded for this reason were not the same across waves (i.e. the participants with negative indices at Wave 1 were not the same participants with negative indices at Wave 2), which meant that our final overall sample was N = 200, composed of 198 participants at Wave 1 (90 men, M_{age}=18.32, SD_{age}=0.96), 185 participants at Wave 2 (83 men, M_{age}=18.64, SD_{age}=1.04), and 177 at Wave 3 (79 men, M_{age}=19.28, SD_{age}=1.00). Participants were paid €60 for each wave and a €60 bonus for completing all waves.

Procedure. Participants were informed the study was about emotions in daily life, but not given information about the expected relationships. There were three waves: Wave 2 occurred 4 months after Wave 1, and Wave 3 occurred 12 months after Wave 1. Data collection for our focal measures was identical across waves. Waves started with a lab session where participants were trained on the experiencing-sampling methodology (ESM) protocol, followed by an ESM phase containing our focal measures.

ESM protocol. Participants completed seven consecutive days of ESM on a research-dedicated smartphone using custom-developed Android software *mobileQ* (Meers, Dejonckheere, Kalokerinos, Rummens, & Kuppens, in preparation). The smartphone signaled 10 times a day during waking hours (10am to 10pm) following a stratified random-interval scheme (waking hours were divided into 10 equal intervals, and a signal sent randomly during each interval). Participants received approximately 70 signals (M=70.5), which were sent on average every 71.7 minutes in Wave 1 (SD=29.2), 71.9 minutes in Wave 2 (SD=29.5), and 72.0 minutes in Wave 3 (SD=29.5). Compliance was good in all three waves (Wave 1 M=87.3%, SD=9.1%; Wave 2 M=87.9%, SD=8.8%; Wave 3 M=88.4%, SD=8.7%).

Measures.

Negative emotion. Six emotions (stressed, angry, sad, anxious, depressed, lonely) were assessed in a randomized order using a 100-point slider scale (0=*not at all*, 100=*very much*). The stem for these items was "how [emotion] do you feel at the moment?" (between-person reliability R_{KF}: Wave 1=.99, Wave 2=.99, Wave 3=.99; within-person reliability R_C: Wave 1=.73, Wave 2=.75, Wave 3=.73). Working from circumplex models of affect (Russell, 1980), we selected these items to represent both low arousal (sad, depressed, lonely) and high arousal (angry, anxious, stressed) negative affect (and checked item fit with Dutch-language valence and arousal norms; Moors et al., 2013). The number and type of negative emotions assessed was consistent with past work on emotion differentiation using multiple assessments (e.g.Barrett et al., 2001; Kashdan et al., 2010; Zaki et al., 2013). Providing validity evidence, in another study using these data, average momentary negative emotion was positively associated with depression, anxiety, and stress, and negatively associated with average momentary positive emotion (Dejonckheere et al., 2018).

Negative emotion differentiation. In line with past work (e.g. Erbas et al., 2018), we used the intra-class correlation (ICC) to measure average consistency between negative emotions across time (Shrout & Fleiss, 1979). We calculated ICCs across measurement occasions within-person and within-wave (resulting in up to three wave-level indices per participant). Reliable ICCs are between 0 and 1, so we excluded 7 uninterpretable negative values (Giraudeau, 1996). As in previous research (Barrett et al., 2001), we normalized ICCs using a Fisher's Z-transformation. We then reverse-scored (-1*ICC), so that higher scores indicated higher differentiation. Providing validity evidence, other research has shown that this negative differentiation index is negatively linked with negative emotion experience, neuroticism, and depression, and positively linked with self-esteem and meta-knowledge about emotions (Erbas, Ceulemans, Pe, Koval, & Kuppens, 2014).

Emotion regulation strategies. We assessed five strategies (adapted from Brans, Koval, Verduyn, Lim, & Kuppens, 2013) using a 100-point slider scale (0=*not at all*, 100=*very much*). Items were preceded by the stem "Since the last beep, have you…", and assessed rumination (averaging together two items: "ruminated about something in the past?" and "ruminated about something in the future?"), distraction ("distracted yourself from your feelings?"), cognitive reappraisal ("looked at the cause of your feelings from another perspective?”), expressive suppression (“suppressed the expression of your emotions?”), and social sharing (“talked to others about your emotions?”). Providing validity evidence, in our previous work using these items, suppression and rumination were associated with increased negative emotion and decreased in positive emotion (Kalokerinos, Résibois, Verduyn, & Kuppens, 2017), and reappraisal, distraction, and sharing were associated with increased positive emotion (Brans et al., 2013).

Data Analytic Strategy

We conducted analyses in R (v3.4.1) using lme4 (Bates, Maechler, Bolker, & Walker, 2015) to fit linear mixed effects models, and calculating p-values using lmerTest (Kuznetsova, Brockhoff, & Christensen, 2013). We ran three-level models, with measurement occasions (N=34,660) nested within waves (N=3) nested within persons (N=200). To account for potential differences between waves and people, these models estimate separate random effects associated with each wave and person, and fixed effects averaging across waves and people. Strategies and emotion were measured at the occasion-level, and emotion differentiation at the wave-level. To illustrate significant interactions we calculated simple slopes (Preacher, Curran, & Bauer, 2006) of strategies at low and high differentiation (1 SD below/above the mean). To aid in interpretability and reduce convergence issues, all variables were standardized.

To estimate effect size, we calculated pseudo-R^2 measures. These should be interpreted with caution, given debate around quantifying variance explained in multilevel models (LaHuis, Hartman, Hakoyama, & Clark, 2014). We used the R^2_{OLS} measure, which is calculated based on how variance is partitioned (LaHuis et al., 2014; we find comparable results with other total explained variance indices). For each predictor, we calculated partial-R^2_{OLS} by subtracting explained variance in a nested model excluding the focal predictor from the explained variance in the full model.

Model 1: Emotion differentiation predicting strategies. Negative emotion was associated with both increased regulation and reduced differentiation. Because we were interested in the relationship independent of these effects, we controlled for wave-level negative emotion. We used differentiation and negative emotion, which were both centered within wave, to predict each strategy separately (5 models), including random intercepts per wave and participant.

Model 2: Emotion differentiation x emotion regulation strategies predicting negative emotion. We used differentiation, regulation, and their cross-level interaction to predict negative emotion (separately for each strategy; 5 models). We also included lagged negative emotion (i.e. at the previous time-point), allowing us to model change in negative emotion as a function of our predictors. We excluded overnight lags.

For regulation and lagged emotion, we person-mean centered within wave (i.e. subtracting the person-mean within that wave from each score). We wave-mean centered differentiation (i.e. subtracting the grand-mean within that wave from each score). We included random intercepts per wave and participant. For each wave and each participant, we included random slopes for regulation and lagged emotion and allowed these slopes to covary. Finally, we included random slopes for waves nested within participants. Thus, these models tested the extent to which the association between the use of a strategy and negative emotion was a function of a person's emotion differentiation. We also ran these models controlling for wave-level negative emotion (as in Model 1), and its interaction with regulation. Our focal effects were unchanged, and so we report the more parsimonious model excluding this variable.

Results

Descriptive statistics are in Table 1, and within- and between-person correlations are in Tables S1 and S2 in the Supplemental Materials (SOM-U).

Model 1. As demonstrated in Table 2, and contrary to Hypothesis 1, differentiation was negatively associated with reappraisal and sharing, and had no significant association with the other strategies. These effects were small, with differentiation explaining .03% of the variance in these two strategies.

Table 1.

Descriptive Statistics by Wave in Study 1.

	Mean			Within-Person Standard Deviation			Between-Person Standard Deviation			ICC		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Emotion differentiation	0.37	0.38	0.40	-	-	-	0.20	0.21	0.21	-	-	-
Rumination	27.36	20.89	21.74	15.46	14.99	15.19	21.56	18.89	19.21	.42	.52	.45
Distraction	30.34	20.36	19.97	18.16	16.76	17.52	25.35	23.01	25.20	.47	.48	.46
Cognitive reappraisal	18.24	15.64	13.67	12.93	13.28	13.13	18.43	17.09	16.92	.35	.37	.37
Expressive suppression	19.84	18.83	17.38	15.75	15.49	15.37	21.91	22.14	20.98	.49	.46	.46
Social sharing	19.12	17.14	16.92	17.37	17.65	17.61	21.08	21.16	21.18	.24	.26	.27
Negative emotion	19.53	13.71	12.56	9.46	8.88	8.68	13.42	12.45	11.33	.42	.45	.42

Notes. ICC = intraclass correlation, which represents the proportion of variance at the between-person level. ICCs and within-person SDs are not provided for differentiation because it is assessed at the between-person level. To aid in interpretability of means, we include the raw scores for differentiation, reverse-coded (i.e. prior to Fisher-Z transformation).

Table 2.

Model 1: Effects of Emotion Differentiation on Emotion Regulation Strategies in Study 1.

	Strategy																			
	Rumination				Distraction				Reappraisal				Suppression				Social sharing			
	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2
Intercept	-0.01 (0.03)	[-0.06, 0.05]	.828		0.001 (0.04)	[-0.07, 0.07]	.971		0.01 (0.03)	[-0.05, 0.06]	.825		-0.01 (0.04)	[-0.07, 0.06]	.897		0.004 (0.03)	[-0.06, 0.06]	.906	
ED	0.002 (0.02)	[-0.03, 0.04]	.915	<.001	0.001 (0.02)	[-0.04, 0.05]	.962	<.001	**-0.06 (0.02)**	**[-0.09, -0.03]**	**<.001**	**.003**	0.01 (0.02)	[-0.04, 0.05]	.798	<.001	**-0.07 (0.01)**	**[-0.10, -0.04]**	**<.001**	**.003**
NE mean	0.47 (0.02)	[0.43, 0.52]	<.001	.22	0.28 (0.03)	[0.23, 0.34]	<.001	.13	0.26 (0.02)	[0.21, 0.30]	<.001	.12	0.33 (0.03)	[0.27, 0.38]	<.001	.13	0.15 (0.02)	[0.11, 0.19]	<.001	.04

Notes. Lines including the effects of interest are shaded grey. Significant effects in these lines are bolded. ED = Emotion differentiation, NE mean = the person mean of negative emotion.

Model 2. As displayed in Table 3, all strategies were associated with increased negative emotion. As we have noted elsewhere, this is likely because in daily life, strategies are implemented to counteract rising negative emotion (Brans et al., 2013), and so strategies occur as negative emotion is already rising. We partially corrected for this by modelling negative emotion at the previous time-point, but because we do not have the temporal resolution to capture every fluctuation precipitating regulation, this approach is not perfect. Study 2 partially addresses this issue by focusing all measurements around a single event.

In line with Hypothesis 2, we found interactions between all strategies and differentiation. In Table 4, we test simple slopes, which are graphed in Figure 1. In line with Hypothesis 2a, all strategies were associated with increased negative emotion among low differentiators. Contrary to Hypothesis 2b, all strategies were also associated with increased negative emotion among high differentiators, although this effect was attenuated compared to low differentiators, supporting Hypothesis 2c. These interactions explained a small portion of the variance in negative emotion (between .03 and 1%).

Secondary analyses. In our previous analyses, we focused on the link between regulation and subsequent negative emotion, but negative emotion can also predict subsequent emotion regulation (Brans et al., 2013). If this direction of effects is driving these results, it could be that when they experience negative emotion, low differentiators are more likely to endorse all strategies more, taking a scattershot approach to regulation. To investigate this idea, we ran a reverse version of Model 2 in which negative emotion predicted changes in regulation as a function of differentiation. We found little evidence for this notion: More details and the full results of these models are included in the Supplemental Reverse Directional Analyses (SOM-R).

To determine whether our results were robust across the specific set of negative emotions included, we ran a leave-one-out multiverse analysis for both models (Steegen, Tuerlinckx, Gelman, & Vanpaemel, 2016). This analysis tested whether results replicated when putatively more complex (e.g. lonely) or less specific (e.g. stressed) emotion terms were included or omitted, and whether results remained robust across alternative selections of emotion items. To create the multiverse, we computed a series of differentiation and negative emotion indices each based on five of the six different emotions assessed, leaving out the sixth emotion. We ran both models across this multiverse of negative emotion, and found our results replicated across 100% of specifications. The details of these analyses are in the Supplemental Materials (Figures S1-S4; SOM-U).

Finally, we replicated results controlling for survey number, and found no change in the results, providing some evidence that our findings were independent from participant fatigue or other time trends.

Table 3.

Model 2: Effects of Interactions between Emotion Differentiation and Emotion Regulation Strategies on Negative Emotion in Study 1.

	Strategy																			
	Rumination				Distraction				Reappraisal				Suppression				Social sharing			
	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*P*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2
Intercept	-0.01 (0.07)	[-0.14, 0.12]	.898		-0.01 (0.07)	[-0.14, 0.12]	.878		-0.01 (0.07)	[-0.14, 0.12]	.883		-0.01 (0.07)	[-0.15, 0.12]	.883		-0.01 (0.07)	[-0.14, 0.12]	.881	
Strategy	0.22 (0.01)	[0.20, 0.24]	<.001	.05	0.13 (0.02)	[0.09, 0.16]	.002	.01	0.11 (0.02)	[0.08, 0.15]	.010	.01	0.18 (0.01)	[0.15, 0.21]	<.001	.02	0.09 (0.01)	[0.07, 0.11]	<.001	.004
ED	-0.14 (0.01)	[-0.16, -0.13]	<.001	.08	-0.14 (0.01)	[-0.16, -0.13]	<.001	.08	-0.14 (0.01)	[-0.16, -0.13]	<.001	.08	-0.14 (0.01)	[-0.15, -0.13]	<.001	.08	-0.14 (0.01)	[-0.16, -0.13]	<.001	.08
Strategy × ED	**-0.10 (0.01)**	**[-0.12, -0.09]**	**<.001**	**.01**	**-0.05 (0.01)**	**[-0.07, -0.04]**	**<.001**	**.003**	**-0.05 (0.01)**	**[-0.07, -0.03]**	**<.001**	**.003**	**-0.09 (0.01)**	**[-0.11, -0.07]**	**<.001**	**.01**	**-0.06 (0.01)**	**[-0.08, -0.04]**	**<.001**	**.003**
Lagged NE	0.19 (0.02)	[0.16, 0.22]	.004	.05	0.22 (0.01)	[0.19, 0.25]	.001	.07	0.23 (0.01)	[0.20, 0.25]	<.001	.07	0.21 (0.01)	[0.18, 0.24]	.001	.06	0.23 (0.01)	[0.20, 0.25]	<.001	.07

Notes. Lines including the effects of interest are shaded grey. Significant effects in these lines are bolded. Strategy = Emotion regulation strategy named at the top of each column. ED = Emotion differentiation, lagged NE = negative emotion at previous time-point.

Table 4.

Simple Slopes of Emotion Regulation Strategies on Emotion at Low (- 1 SD) and High (+ 1 SD) Emotion Differentiation in Study 1.

	Low Emotion Differentiation (- 1 SD)			**High Emotion Differentiation (+ 1 SD)**		
	Estimate (SE)	95% CI	*p*	Estimate (SE)	95% CI	*p*
Rumination	0.32 (0.01)	[0.30, 0.34]	<.001	0.12 (0.01)	[0.10, 0.14]	<.001
Distraction	0.18 (0.02)	[0.14, 0.22]	<.001	0.07 (0.02)	[0.03, 0.11]	<.001
Cognitive reappraisal	0.16 (0.02)	[0.12, 0.20]	<.001	0.07 (0.02)	[0.03, 0.11]	.002
Expressive suppression	0.27 (0.02)	[0.23, 0.31]	<.001	0.09 (0.02)	[0.05, 0.13]	<.001
Social sharing	0.15 (0.01)	[0.13, 0.17]	<.001	0.03 (0.02)	[0.00, 0.06)	.047

Notes. Degrees of freedom (N-k-1) are 195.

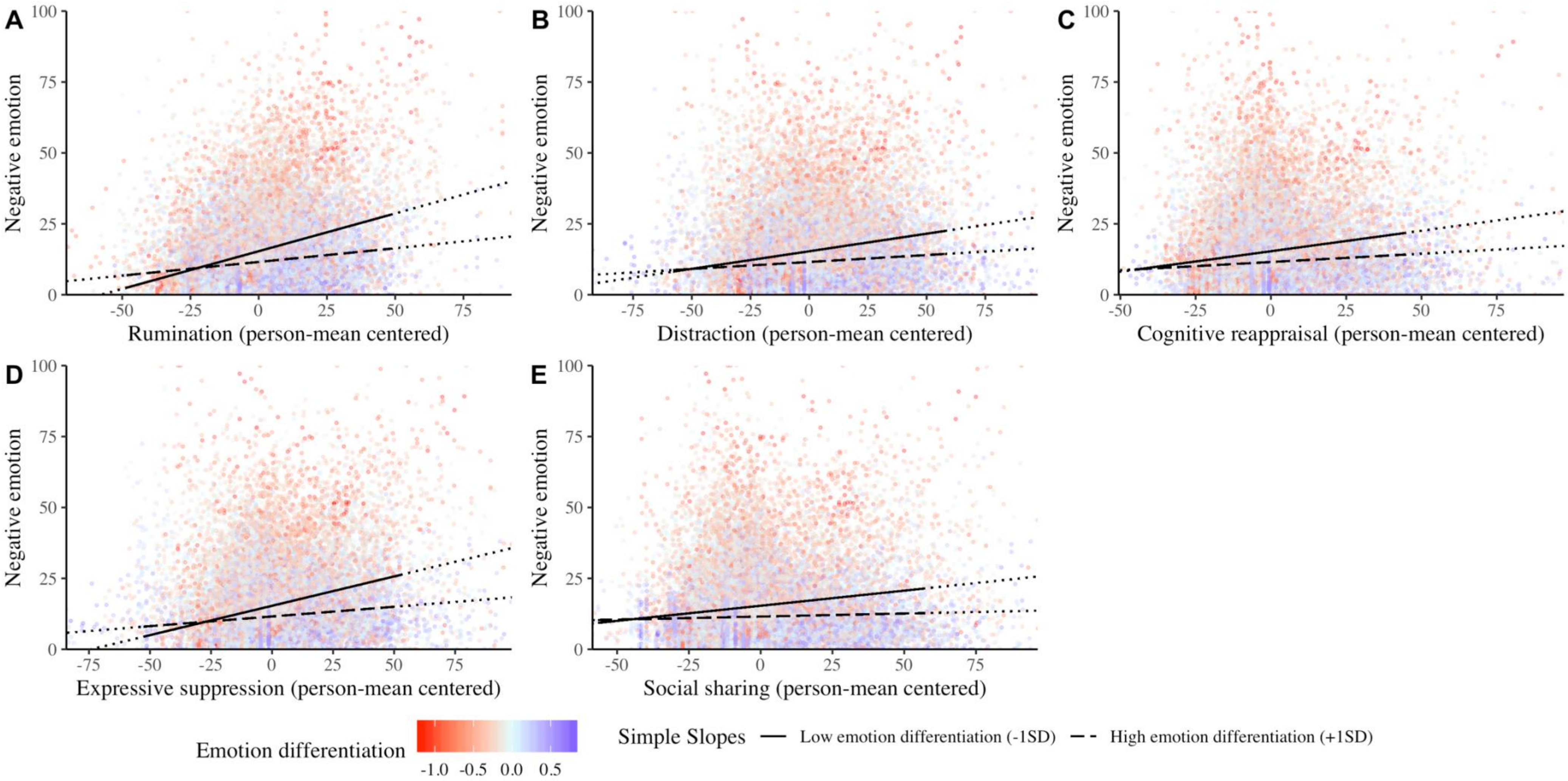

Figure 1. Graphs of the significant emotion regulation strategy x emotion differentiation interactions on the change in negative emotion in Study 1: Rumination (Panel A), Distraction (Panel B), Reappraisal (Panel C), Suppression (Panel D), and Sharing (Panel E). Analyses are conducted with standardized coefficients, but graphs use unstandardized coefficients for interpretability (graphs using standardized coefficients are available in Supplemental Materials Figure S9; SOM-U). Scatterplot points represent each momentary observation colored by person-level emotion differentiation (red = low differentiation, blue = high differentiation; note that emotion differentiation is Fisher-Z transformed). Dotted lines are used when the estimated simple slopes are +/- 3 standard deviations from the mean of the predictor (emotion regulation strategies) to represent the uncertainty in these estimates given relatively few observations. Emotion regulation strategies are person-mean centered within wave, so we examine deviations around each individual's mean strategy intensity within that wave.

Study 2

We designed this study around an emotional event for two reasons. First, Study 1 examined everyday life, in which few emotional events may occur. Differentiation may be more important in emotional events necessitating stronger regulation. Second, in Study 1, we could not fully account for the emotional triggers underlying emotion regulation and experience. In Study 2, items center around a single event, allowing us to better model the temporal trajectory.

Method

These data were part of a larger study which received ethical approval from the KU Leuven ethics committee. We discuss only the measures analyzed for the current study. These data have not yet been used to test other research questions.

Participants were 101 Belgian first-year psychology students receiving results from their first semester (14 men; M_{age}=18.64; SD_{age}=1.45). Belgium has almost unrestricted access to university: strong selection takes place in the first year, rather than before enrollment. This means that first semester results are crucial for students' academic futures, and receiving results is a highly personally-relevant event. Five first-year psychology subjects were offered, and most participants took all five (N=92, 91.1%). We aimed to recruit at least 100 students (of approximately 400 new enrolments), allowing us more than 80% power to detect medium-sized effects (r=.30, α=.05). We recruited at a first-year research participation session and using social media. All participants had more than 50% compliance, so no participants were omitted. Participants received 50 euros for completing at least 80% of the ESM, and 5 euros less for every 10% drop in compliance.

Procedure. Three days before receiving results, participants came to a lab session where they were trained on the ESM protocol. Participants were told that the study was about emotions and exams, but not given details about specific hypotheses. They then completed the ESM phase. On results release day, within a two-hour period, students were notified by email that results were available in an online portal and asked to check them immediately. On this day, participants were sent a link to an online survey asking them to report their grade for each subject.

ESM protocol. Participants with a compatible personal Android phone installed *mobileQ* (N=28). Other participants were given a research-only smartphone (N=73). Participants completed 9 consecutive days of ESM: 2 days before, and 7 days after results release. We used a stratified random-interval scheme, sending a random signal within 10 equal intervals between 10am and 10pm. There was some variability in when results were released: Participants received their results between surveys 21 and 28 of 90. In this research, we were interested in regulation in response to results, and thus only include post-results surveys, meaning that participants received between 63 and 70 surveys (*M*=68.69). Participants received a signal on average every 71.9 minutes (*SD*=29.8), and completed an average of 90.5% of signals (*SD*=7.8%).

Materials and measures.

Negative emotion. Six emotions (sad, angry, disappointed, ashamed, anxious, stressed) were assessed on a 100-point scale (1=*not at all,* 100=*very much*). The item stem was “when you think about your grades right now, how [emotion] are you feeling?” (R_{KF}=.99;R_{C}=.74). In this study, we updated this measure to include emotions relevant the context of receiving learning outcomes (Pekrun, 2006). We kept sadness, anger, anxiety, and stress from Study 1, as the former three are also learning-related emotions (Pekrun, 2006) and continuity across studies allowed for comparison. However, differentiation should replicate across the inclusion of different emotions if each of the emotions provides new information. We added disappointment and shame because of their centrality in retrospectively evaluating learning outcomes (Pekrun, 2006).

Negative emotion differentiation. As per Study 1, we took the ICC between negative emotions within-person across measurement occasions, Fisher-Z transformed it, and reverse-scored so that higher numbers equaled higher differentiation. There were no negative ICCs.

Emotion regulation. We assessed six strategies on a 7-point scale (0=*not at all,* 6=*very much)*. The item stem was “Since the last beep, have you…”. Five strategies from Study 1 were reworded to assess grade-relevant regulation: rumination (“ruminated about your grades?”), distraction (“distracted yourself from your grades and the associated emotions?”), reappraisal (“looked at your grades or the emotions that go with them from another perspective?”), expressive suppression (“suppressed the outward expression of your emotions about your grades?”), and social sharing (“talked to others about your grades and the associated emotions?”). We also included acceptance (“accepted your emotions about your grades the way they are?”).

Percentage passed. For each subject, participants reported scores out of 20, with 10 and above being a pass, and below 10 a fail. Failing requires retaking the exam later in the year or, in case of too many fails, termination of enrollment. Given the clear emotional line at passing, we dichotomized scores on each subject as fail (1-9) or pass (10-20) and calculated the percentage of subjects passed across all subjects taken. This percentage variable was highly correlated with mean score out of 20 across exams (r=.90), and we found no differences in reported results when using mean score instead of percentage passed.

In the baseline survey, we assessed participants expectations about their upcoming exam grade using the same measure. We used this to compute an *expected percentage passed* variable. Including both expected and actual pass percentage, or the difference between actual and expected pass percentage, did not substantively change our results. Thus, we focus on actual pass percentage.

Data Analytic Strategy

As in Study 1, we used lme4 (Bates et al., 2015) to fit mixed effects models, and standardized variables for analyses. We ran two-level models, with measurement occasions (N= 6,282) nested within persons (N=101). In these models, we included percentage pass as a proxy for emotional intensity of the stimulus. However, since we do not have the necessary statistical power, we do not estimate a three-way interaction with this variable. Strategies and negative emotion were measured at the occasion-level, and differentiation and percentage passed at the person-level. We found no substantive differences in either model when person-level negative emotion was included, but we include this variable in Model 1 to replicate Study 1.

Model 1: Emotion differentiation predicting strategies. We used differentiation, percentage passed, and negative emotion, which were grand-mean centered, to predict each strategy separately (6 models). We included random intercepts per participant.

Model 2: Emotion differentiation x emotion regulation strategies predicting negative emotion. We used differentiation, regulation, their cross-level interaction, and percentage passed to predict negative emotion (separately for each strategy; 6 models). We include lagged negative emotion (at the previous time-point) to model emotional change, again excluding overnight lags. We person-mean centered regulation and lagged emotion, and grand-mean centered differentiation and percentage passed. We included random intercepts per participant. For each participant, we included random slopes for regulation and lagged emotion and allowed these slopes to covary. There was one exception to this strategy: the acceptance model would not converge until we removed the random slope for acceptance, so we report this model with this random slope omitted.

Results

Descriptive statistics are in Table 5, and within- and between correlations are in Table S3 in the Supplemental Materials (SOM-U).

Model 1. As demonstrated in Table 6, partially supporting Hypothesis 1, differentiation was negatively associated with rumination, suppression, and sharing, but not with the other strategies. High differentiators may use putatively maladaptive strategies less in emotional events. These effects were small, with differentiation explaining between 1-3% of the variance.

Table 5.

Descriptive Statistics in Study 2.

	Mean	Within-Person Standard Deviation	Between-Person Standard Deviation	ICC
Emotion differentiation	.37	-	.22	-
Percentage passed	55.79	-	34.73	-
Rumination	3.67	0.97	2.25	.42
Distraction	1.30	0.78	1.71	.65
Cognitive reappraisal	2.11	0.75	2.16	.48
Acceptance	3.91	1.16	2.20	.62
Expressive suppression	1.24	0.62	1.70	.58
Social sharing	4.14	1.33	1.95	.21
Negative emotion	31.44	7.25	26.84	.85

Notes. ICC = intraclass correlation, which represents the proportion of variance at the between-person level. ICCs and within-person standard deviations are not provided for variables assessed only at the between-person level (emotion differentiation and percentage passed). To aid in interpretability of means, in this table we include the raw scores for emotion differentiation (without the Fisher-Z transformation), reverse-scored.

Table 6.

Model 1: Effects of Emotion Differentiation on Emotion Regulation Strategies in Study 2.

	Strategy																							
	Rumination				Distraction				Reappraisal				Acceptance				Suppression				Social sharing			
	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2
Intercept	0.002 (0.05)	[-0.11, 0.11]	.968		-0.01 (0.08)	[-0.16, 0.15]	.932		-0.004 (0.07)	[-0.13, 0.27]	.952		0.003 (0.07)	[-0.13, 0.14]	.965		0.002 (0.07)	[-0.13, 0.14]	.975		-0.002 (0.04)	[-0.09, 0.09]	.958	
ED	**-0.13 (0.06)**	**[-0.24, -0.02]**	**.019**	**.02**	0.04 (0.08)	[-0.12, 0.20]	.605	.002	-0.07 (0.07)	[-0.20, 0.06]	.292	.004	0.10 (0.07)	[-0.04, 0.24]	.164	.01	**-0.16 (0.07)**	**[-0.30, -0.03]**	**.021**	**.03**	**-0.09 (0.05)**	**[-0.18, -0.01]**	**.042**	**.01**
% pass	0.02 (0.07)	[-0.12, 0.16]	.758	<.001	-0.07 (0.10)	[-0.27, 0.13]	.503	.01	-0.05 (0.08)	[-0.21, 0.12]	.575	.002	-0.11 (0.09)	[-0.29, 0.06]	.207	.01	0.05 (0.09)	[-0.12, 0.22]	.590	.001	0.12 (0.06)	[0.01, 0.23]	.040	.01
NE mean	0.35 (0.07)	[0.21, 0.49]	<.001	.07	0.07 (0.10)	[-0.13, 0.27]	.486	.001	0.17 (0.08)	[0.001, 0.33]	.051	.01	-0.43 (0.09)	[-0.60, -0.26]	<.001	.11	0.34 (0.09)	[0.17, 0.51]	<.001	.07	0.18 (0.06)	[0.07, 0.29]	.002	.02

Notes. Lines including the effects of interest are shaded grey. Significant effects in these lines are bolded. ED = Emotion differentiation, NE mean = the person mean of negative emotion. % pass = percentage of exams passed.

Model 2. As demonstrated in Table 7, rumination, suppression, and sharing were positively associated with negative emotion. Acceptance was negatively associated with negative emotion, and reappraisal and distraction had no significant association. This is in contrast to Study 1, where all strategies were associated with negative emotion. This is likely because in Study 2, all measurement was linked to an event accounted for in analyses, better modeling the antecedents of regulation.

In line with Hypothesis 2, we found interactions between differentiation and rumination, distraction, acceptance, and sharing (but not reappraisal or suppression). In Table 8, we test simple slopes, which are graphed in Figure 2. In line with Hypothesis 2a, there was a positive association between rumination, distraction, and sharing and negative emotion for low differentiators. Partially supporting Hypothesis 2c, for high differentiators, there was no link between any strategy and negative emotion, but there was no evidence for a negative link as per Hypothesis 2b. Finally, there was an unexpected negative association between acceptance and negative emotion for low but not high differentiators. These interactions explained a small portion of the variance in negative emotion (0.1%).

Secondary analyses. As in Study 1, we conducted two sets of secondary analyses. First, we examined the reverse direction of effects in Model 2, and again found little evidence for this idea: see the Supplemental Reverse Directional Analyses (SOM-R) for the full results. Second, we conducted a leave-one-out multiverse analysis for negative emotion. For Model 1, we found significant relationships between differentiation and rumination in 83.3% of models, suppression in 66.7% of models, and sharing in 50% of models. For Model 2, we found significant interactions between differentiation and rumination in 16.7% of models, distraction in 83.3% of models, acceptance in 100% of models, and sharing in 100% of models. This suggests that the interaction with rumination is not robust across emotions included. For more detail, see the Supplemental Materials (Figures S5-S8; SOM-U).

Summary. Table 9 provides a summary of results across studies.

Table 7.

Model 2: Effects of Interactions between Emotion Differentiation and Emotion Regulation Strategies on Negative Emotion in Study 2.

	Strategy																							
	Rumination				Distraction				Reappraisal				Acceptance				Suppression				Social sharing			
	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2	Estimate (SE)	95% CI	*p*	Partial R^2
Intercept	<-0.001 (0.07)	[-0.15, 0.15]	.9996		-0.003 (0.07)	[-0.15, 0.14]	.967		-0.003 (0.07)	[-0.15, 0.14]	.965		-0.004 (0.07)	[-0.15, 0.14]	.957		-0.003 (0.07)	[-0.15, 0.14]	.969		-0.002 (0.07)	[-0.15, 0.14]	.977	
Strategy	0.08 (0.01)	[0.06, 0.11]	<.001	.01	0.02 (0.01)	[0.01, 0.04]	.018	<.001	0.02 (0.01)	[0.003, 0.04]	.026	.001	-0.04 (0.01)	[-0.06, -0.02]	.001	<.001	0.04 (0.01)	[0.02, 0.06]	<.001	.002	0.04 (0.01)	[0.02, 0.05]	<.001	.001
ED	-0.02 (0.08)	[-0.17, 0.13]	.775	<.001	-0.04 (0.07)	[-0.18, 0.11]	.640	<.001	-0.03 (0.07)	[-0.18, 0.12]	.692	<.001	-0.04 (0.07)	[-0.19, 0.10]	.553	<.001	-0.03 (0.07)	[-0.18, 0.11]	.653	<.001	-0.03 (0.07)	[-0.18, 0.11]	.670	<.001
% pass	-0.58 (0.07)	[-0.73, -0.44]	<.001	.31	-0.57 (0.07)	[-0.72, -0.43]	<.001	.31	-0.58 (0.07)	[-0.72, -0.43]	<.001	.31	-0.58 (0.07)	[-0.72, -0.43]	<.001	.31	-0.58 (0.07)	[-0.73, -0.44]	<.001	.31	-0.59 (0.07)	[-0.73, -0.44]	<.001	.31
Strategy x ED	**-0.02 (0.01)**	**[-0.05, -0.001]**	**.041**	**.001**	**-0.03 (0.01)**	**[-0.04, -0.01]**	**.011**	**.001**	-0.02 (0.01)	[-0.04, 0.004]	.127	<.001	**0.03 (0.01)**	**[0.01, 0.05]**	**.003**	**.001**	-0.02 (0.01)	[-0.04, 0.002]	.092	<.001	**-0.03 (0.01)**	**[-0.05, -0.01]**	**<.001**	**.001**
Lagged NE	0.14 (0.01)	[0.12, 0.16]	<.001	.01	0.16 (0.01)	[0.14, 0.18]	<.001	.02	0.16 (0.01)	[0.14, 0.18]	<.001	.02	0.16 (0.01)	[0.14, 0.18]	<.001	.02	0.16 (0.01)	[0.14, 0.18]	<.001	.02	0.16 (0.01)	[0.14, 0.18]	<.001	.02

Notes. Lines including the effect of interest are shaded grey. Significant effects in these lines are bolded. Strategy = Emotion regulation strategy named at the top of each column. ED = Emotion differentiation, NE mean = the person mean of negative emotion. % pass = percentage of exams passed. Lagged NE = negative emotion at previous time-point.

Table 8.

Simple Slopes of Emotion Regulation Strategies on Emotion at Low (- 1 SD) and High (+ 1 SD) Emotion Differentiation in Study 2.

	Low Emotion Differentiation (- 1 SD)			**High Emotion Differentiation (+ 1 SD)**		
	Estimate (SE)	95% CI	*p*	Estimate (SE)	95% CI	*p*
Rumination	0.11 (0.02)	[0.07, 0.15]	<.001	0.06 (0.02)	[0.02, 0.10]	.001
Distraction	0.05 (0.01)	[0.03, 0.07]	<.001	-0.001 (0.01)	[-0.02, 0.02]	.958
Acceptance	-0.07 (0.01)	[-0.09, -0.05]	<.001	-0.01 (0.02)	[-0.05, 0.03]	.711
Social Sharing	0.07 (0.01)	[0.05, 0.09]	<.001	0.01 (0.01)	[-0.01, 0.03]	.543

Notes. Simple slopes were only calculated for significant interactions. Degrees of freedom (N-k-1) are 95.

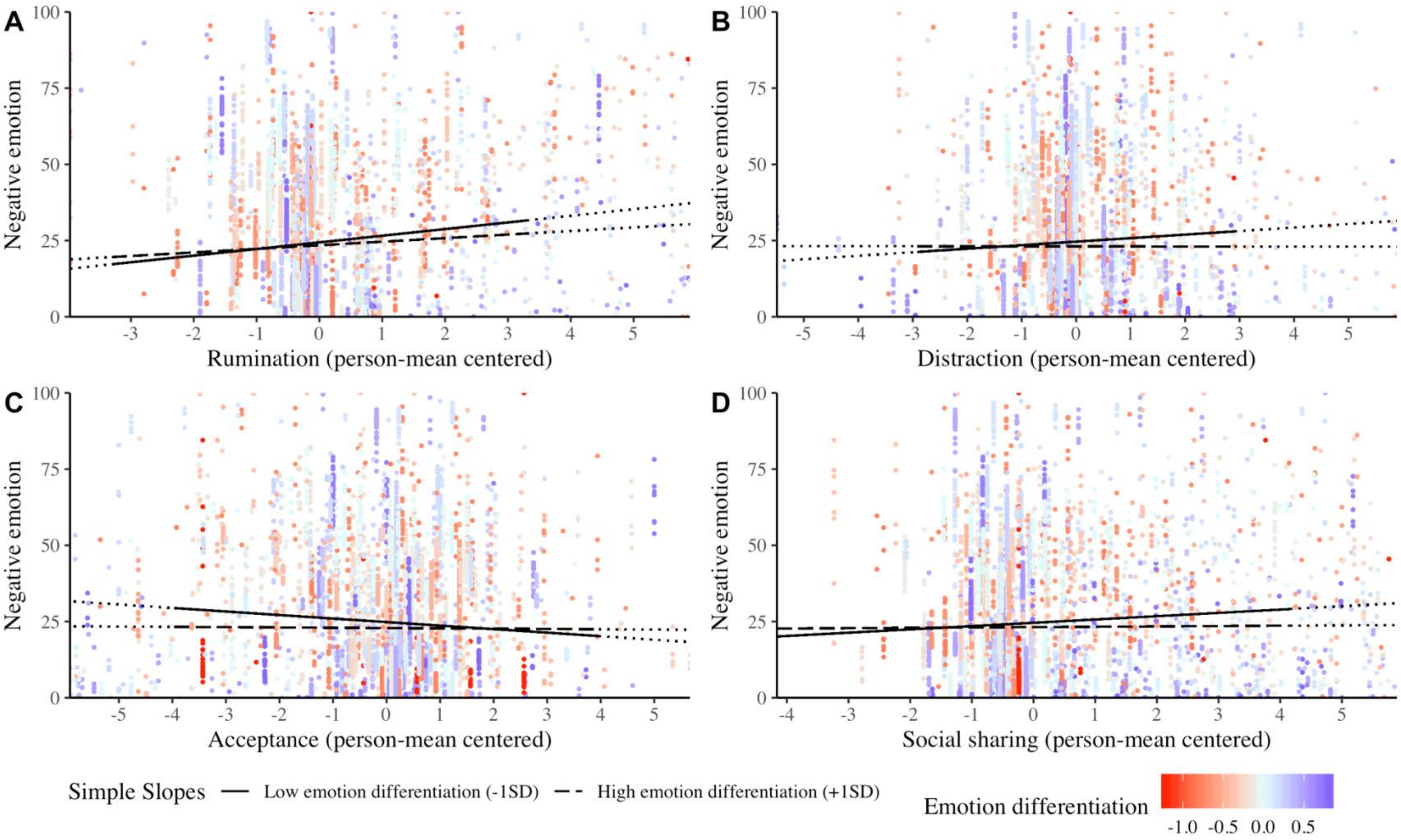

Figure 2. Graphs depicting the significant emotion regulation strategy x emotion differentiation interactions on the change in negative emotion in Study 1: Rumination (Panel A), Distraction (Panel B), Acceptance (Panel C), and Sharing (Panel D). Analyses are conducted with standardized coefficients, but graphs use unstandardized coefficients for interpretability (graphs using standardized coefficients are available in Supplemental Materials Figure S10; SOM-U). Scatterplot points represent each momentary observation colored by person-level emotion differentiation (red = low differentiation, blue = high differentiation; note that emotion differentiation is Fisher-Z transformed). Dotted lines are used when the estimated simple slopes are +/- 3 standard deviations from the mean

of the predictor (emotion regulation strategies) to represent the uncertainty in these estimates given relatively few observations. Emotion regulation strategies are person-mean centered, so we examine deviations around each individual's mean strategy intensity.

Table 9.

Summary of Significant (p < .05) Strategy-Specific Associations with Emotion Differentiation across Studies 1 and 2.

	Hypothesis	Study 1 (N = 200, three waves)	Study 2 (N = 101, post-exam results)
Model 1 (Strategy Selection): Emotion differentiation on strategies			
Rumination	Negative association	No significant association	Negative association
Distraction	No hypothesis	No significant association	No significant association
Cognitive reappraisal	Positive association	Negative association	No significant association
Expressive suppression	Negative association	No significant association	Negative association
Social sharing	No hypothesis	Negative association	Negative association
Acceptance	Positive association	*Not assessed*	No significant association
Model 2 (Strategy Effectiveness): Emotion differentiation x strategy interaction on negative emotion			
Rumination	Interaction	Interaction	Interaction
Distraction	Interaction	Interaction	Interaction
Cognitive reappraisal	Interaction	Interaction	No significant association
Expressive suppression	Interaction	Interaction	No significant association
Social sharing	Interaction	Interaction	Interaction
Acceptance	Interaction	*Not assessed*	Interaction

Discussion

It has been argued that differentiating between emotions provides information that could facilitate effective emotion regulation (Barrett & Gross, 2001). Given deficits in both differentiation and regulation are associated with psychopathology, determining the existence and nature of the link between these constructs is of both practical and theoretical importance. Across two experience-sampling studies, six strategies, and two regulatory processes, we conducted the first comprehensive test of this link. Broadly, we found evidence that differentiation is associated with strategy effectiveness, but not selection.

Strategy Selection

Contrary to Hypothesis 1, we found few links between differentiation and strategy selection. The only consistency across studies was a negative association with social sharing. Unexpectedly, differentiation was associated with reduced reappraisal in Study 1 (but not Study 2) and as hypothesized, with reduced suppression and rumination in Study 2 (but not Study 1). It may be that links between differentiation and maladaptive strategies emerge only within emotional events, where regulation difficulties are exacerbated. However, taken together, these findings suggest that differentiation is not strongly implicated in strategy selection. Links between differentiation and selection may be inconsistent because we examined chronic strategy endorsement, rather than flexible selection. Recent perspectives have suggested that strategies are not inherently adaptive or maladaptive, instead emphasizing context-sensitivity in selection (Bonanno & Burton, 2013).

In previous work, differentiation was positively associated with retrospective emotion regulation aggregated across strategies (Barrett et al., 2001), but any links we found between differentiation and strategies were negative. This highlights the difference between momentary and retrospective assessment. Higher differentiators might report more retrospective regulation because emotional precision facilitates memory. However, in daily life, they may regulate less intensely.

Strategy Effectiveness

Supporting Hypothesis 2, we found links between differentiation and effectiveness for all strategies in Study 1, and for 4 of 6 strategies in Study 2. As per Hypothesis 2a, in low differentiators, both adaptive and maladaptive strategies were more strongly associated with increased negative emotion, suggesting cross-strategy deficits. The exception was acceptance, which was associated with reduced negative emotion for low differentiators: however, this effect could reflect costs of non-acceptance, rather than benefits of acceptance. In high differentiators, we found an attenuated relationship between strategies and negative emotion. This was in line with the pattern predicted for maladaptive strategies in Hypothesis 2c. However, contradicting Hypothesis 2b, adaptive strategies were not associated with decreased negative emotion in high differentiators.

This may indicate that emotion regulation backfires for low differentiators, rather than improving among high differentiators. However, it could also be that high differentiators are effectively counteracting natural emotional increases. That is, they are neutralizing emotion that was already increasing, rather than entirely reversing the emotional trajectory. This interpretation would suggest benefits to high differentiation but cannot be tested in our data: this would require an experimental design with a control condition.

Although effectiveness results were generally robust across strategies and datasets, they were small in size. These effect sizes compare with the median interaction effect in applied psychology (Aguinis, Beaty, Boik, & Pierce, 2005), and interaction effects are usually small, particularly when they involve an attenuation rather than a reversal (Wahlsten, 1991). Nonetheless, accounting for small effect sizes will be important for follow-up work and intervention.

Implications and Future Directions

These studies are the first to consider several strategies separately, and to test multiple regulatory processes. In doing so, they provide an empirical foundation for theory suggesting that effective regulation underlies the benefits of differentiation (Kashdan et al., 2015; Smidt & Suvak, 2015). Extending theory, we found it matters *which part* of the regulation process is considered. There were consistent links between differentiation and effectiveness, but not selection, suggesting process-specific deficits.

Both differentiation deficits and regulation difficulties have been suggested as constructs underpinning psychopathology. Their link suggests a role for differentiation training in facilitating regulation in clinical populations. In particular, in Study 2, acceptance was associated with reduced negative emotion among low differentiators. Thus, one effective intervention may be mindfulness, which aims to increase acceptance, and has been associated with differentiation (Van der Gucht et al., 2018).

We did not test mechanisms, but view this as an important next step. Based on prior research, we suggest four potential mechanisms. First, differentiation is associated with reduced overlap between emotional appraisals (Erbas, Ceulemans, Koval, & Kuppens, 2015).

This suggests differentiation may assist in understanding the cause of emotion, facilitating contextually-sensitive regulation (Bonanno & Burton, 2013). Second, strategies may be differentially effective for specific emotions (e.g. Rivers, Brackett, Katulak, & Salovey, 2007), and so differentiated emotions may allow for the selection of more effective strategies. However, our data do not support strategy-specific processes. Third, specific emotions may enable clearer emotion regulation goals (e.g. I want to feel less sad, rather than I want to feel better; Mauss & Tamir, 2014). Finally, differentiation may facilitate other processes that assist in regulation: for example, discounting incidental emotional information (Cameron, Payne, & Doris, 2013).

Limitations

First, participants were Belgian students, which constrains the generalizability of results. Given differentiation difficulties in psychopathology (Smidt & Suvak, 2015), it will be important to replicate in clinical samples. Second, because experience-sampling necessitates brevity, we did not include all potential specific emotions. We selected items based on theory, but there is no standard set of emotions to assess differentiation, and some items were potentially complex (e.g. lonely) or imprecise (e.g. stressed). The multiverse analysis demonstrated that our results were generally robust to the removal of emotion items, and theoretically, differentiation should generalize across emotions if each provides additional information. However, future measurement work is necessary.

Finally, although we controlled for prior emotion, our analyses were correlational, so we cannot determine whether regulation *caused* emotion. Effects could run in the opposite direction, such that when they feel negative, low differentiators are more likely to use all strategies. We conducted reverse directional analyses which provided little evidence for this idea. However, with correlational data, such analyses cannot be conclusive.

Conclusions

We found that emotion differentiation was not consistently associated with emotion regulation strategy selection, but low differentiation inhibited strategy effectiveness. Among low differentiators, strategies were associated with increased negative emotion, but among high differentiators, this relationship was attenuated. In all, these studies provide empirical evidence for the theoretical place of differentiation in the regulation process, and suggest the possibility of training differentiation to address regulation difficulties.

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Author Contributions

Elise Kalokerinos and Yasemin Erbas developed the study concept with input from Peter Kuppens and Eva Ceulemans. The data was collected in part by Elise Kalokerinos and Yasemin Erbas. Elise Kalokerinos performed the data analysis and interpretation with input from all authors. Elise Kalokerinos and Yasemin Erbas drafted the manuscript, and Peter Kuppens and Eva Ceulemans provided critical revisions. All authors approved the final version of the manuscript.

Open Practices Statement

The two studies reported in this manuscript were not formally preregistered. The data, materials, code-book, and analytic code used in these studies are available on the Open Science Framework at osf.io/bmaf2

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