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Differentiate to Regulate: Low Negative Emotion Differentiation Is Associated With Ineffective Use but Not Selection of Emotion-Regulation Strategies

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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 (a) the selection of emotion-regulation strategies and (b) the effectiveness of these strategies in downregulating negative emotion (*N*s = 200 and 101 participants and 34,660 and 6,282 measurements, respectively). 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 four of six strategies (Study 2) were more strongly associated with increased negative emotion than they were among high differentiators. This suggests that low differentiation may hinder successful emotion regulation, which in turn supports the idea that effective regulation may underlie differentiation benefits.

Keywords
emotions, emotional control, experience sampling, emotion differentiation, emotion regulation, open data, open materials

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Sometimes you feel awful, but you cannot put your finger on any particular feeling—you feel angry, sad, and anxious all at once. At such 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 emotion regulation. This idea is central to theory but has not yet been empirically verified. We tested this idea in two experience-sampling studies, investigating the associations between differentiation and the selection and effectiveness of emotion-regulation strategies.

Affect is generalized, rather than context specific. In this respect it differs from discrete emotions, which deliver unique contextual information (Schwarz, 2012). 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

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ways in which discrete emotional information could assist in regulation. For example, discrete emotions provide information about emotional cause and context, directing regulation toward 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 emotional 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 has tested this deeper link. Barrett, Gross, Christensen, and Benvenuto (2001) asked 53 people to retrospectively report how much they had used nine regulation strategies over the previous 2 weeks and averaged these strategies as an index of regulation. For the next 2 weeks, participants reported their emotion during their most negative daily experience, and their responses were 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 indeed associated with increased regulation, but it was limited in two respects. First, the researchers 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, the researchers did not investigate how effectively regulation shapes subsequent emotional outcomes. Given that theory is centered around effective regulation, rather than increased regulation, such a test is crucial.

Here, we examined how negative emotion differentiation relates to both the selection and effectiveness of emotion-regulation strategies. We focused specifically on negative differentiation because it has been more consistently linked with well-being than positive differentiation (Kashdan et al., 2015). We took 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 are often seen as maladaptive (Gross & John, 2003; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). In contrast, reappraisal and acceptance are positively associated with well-being and are 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 it was 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 pattern of effects 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. Data, code, and materials for both studies are available at osf.io/bmaf2.

Study 1

Method

The data used in this study were drawn from a larger study that received approval from the KU Leuven Ethics Committee. We discuss the measures analyzed only 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 at osf.io/bmaf2.

Participants. 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 this study was designed to test several diverse processes for other projects. Potential participants completed the Center for Epidemiologic Studies Depression (CES-D) 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 participants at Wave 1, 191 at Wave 2, and 178 at Wave 3. Two participants had poor compliance with the momentary surveys at Wave 1 (> 50% of surveys completed) and were thus omitted from the final sample because of concerns about low-quality responding (although results were identical with these participants included). One of these participants completed Wave 1 only; the other 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 Wave 3 (see below for more details). This left us with 200 participants at Wave 1, 190 at Wave 2, and 177 at Wave 3.

We also 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, which meant that our final overall sample consisted of 200 participants: 198 at Wave 1 (90 men; age: M = 18.32, SD = 0.96), 185 at Wave 2 (83 men; age: M = 18.64, SD = 1.04), and 177 at Wave 3 (79 men; age: M = 19.28, SD = 1.00). Participants were paid €60 for each wave and a €60 bonus for completing all waves.

Procedure. Participants were informed that the study was about emotions in daily life, but they were 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 in which participants were trained on the experience-sampling methodology (ESM), followed by an ESM phase containing our focal measures.

ESM protocol. Participants completed seven consecutive days of experience sampling on a research-dedicated smartphone using a custom-developed Android software called mobileQ (Meers, Dejonckheere, Kalokerinos, Rummens, & Kuppens, 2019). The smartphone signaled 10 times a day during waking hours (10:00 a.m. to 10:00 p.m.) following a stratified random-interval scheme (waking hours were divided into 10 equal intervals, and a signal was sent randomly during each interval). Participants received approximately 70 signals (M = 70.5), which were sent on average every 71.7 min in Wave 1 (SD = 29.2), 71.9 min in Wave 2 (SD = 29.5), and 72.0 min 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, or R_{KF}—Wave 1: R_{KF} = .99, Wave 2: R_{KF} = .99, Wave 3: R_{KF} = .99; within-person reliability, or R_C—Wave 1: R_C = .73, Wave 2: R_C = .75, Wave 3: R_C = .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). 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, which provided evidence of these items' validity (Dejonckheere et al., 2018).

Negative-emotion differentiation. Following past work (e.g., Erbas et al., 2018), we used the intraclass correlation coefficient (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 seven 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 them (−1 × ICC), so higher scores indicated higher differentiation. 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 . . ." They 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?"). In our previous work using these items, suppression and rumination were associated with increased negative emotion (Kalokerinos, Résibois, Verduyn, & Kuppens, 2017), and reappraisal, distraction, and sharing were associated with increased positive emotion (Brans et al., 2013), which provides evidence of their validity.

Data-analytic strategy

We conducted analyses in R (Version 3.4.1) using *lme4* (Bates, Mächler, Bolker, & Walker, 2015) to fit linear mixed-effects models, and we calculated p values using *lmerTest* (Kuznetsova, Brockhoff, & Christensen, 2017). 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, we constructed these models to estimate separate random effects associated with each wave and person and to estimate fixed effects averaged across waves and people. Strategies and emotion were measured at the occasion level, and emotion differentiation was measured 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 and above the mean). To aid in interpretability and reduce convergence issues, we standardized all variables.

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 ordinary-least-squares R^2 (R^2_{OLS}) measure, which is calculated on the basis of how variance is partitioned (LaHuis et al., 2014; we found comparable results with other indices of total explained variance). 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 as a predictor of emotion-regulation 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 in Model 1. We used differentiation and negative emotion, which were both centered within wave, to predict each strategy separately (five models), including random intercepts per wave and participant.

Model 2: Emotion Differentiation × Emotion-Regulation Strategies predicting negative emotion. In Model 2, we used differentiation, regulation, and their cross-level interaction to predict negative emotion (separately for each strategy; five 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., we subtracted the person mean within that wave from each score). We wave-mean-centered differentiation (i.e., we subtracted 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, so we report the more parsimonious model excluding this variable.

Results

Descriptive statistics are shown in Table 1, and within- and between-person correlations are shown in Tables S1 and S2 in the Supplemental Material available online.

Model 1. As shown 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 0.03% of the variance in these two strategies.

Model 2. As demonstrated in Table 3, all strategies were associated with increased negative emotion. We have noted elsewhere that this is likely because in daily life, strategies are implemented to counteract rising negative emotion (Brans et al., 2013), so strategies occur as negative emotion is already rising. We partially corrected for this by modeling negative emotion at the previous time

Table 1. Descriptive Statistics by Wave in Study 1

	Mean			Within-person standard deviation			Between-person standard deviation			Intraclass correlation coefficient		
Variable	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	.37	.38	.40	—	—	—	.20	.21	.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

Note: Intraclass correlation coefficients (ICCs) represent the proportion of variance at the between-person level. ICCs and within-person standard deviations are not provided for differentiation because it was assessed at the between-person level. To aid in interpretability of means, we include the raw scores (i.e., prior to Fisher's z transformation) for emotion differentiation, reverse scored.

point, but this approach was not perfect, because we did not have the temporal resolution to capture every fluctuation in negative emotion precipitating regulation. Study 2 partially addressed 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 show the results of simple-slopes analyses, 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 with low differentiators, supporting Hypothesis 2c. These interactions explained a small portion of the variance in negative emotion (between 0.03% and 1%).

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

Table 2. Results From Model 1: Effects of Variables Predicting Emotion-Regulation Strategies in Study 1

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

Note: Boldface indicates significant effects in the variable of interest. CI = confidence interval.

Table 3. Results From Model 2: Effects of Variables Predicting Negative Emotion in Study 1

Strategy and predictor	Estimate (*SE*)	95% CI	*p*	Partial R^2
Rumination				
Intercept	−0.01 (0.07)	[−0.14, 0.12]	.898	
Strategy	0.22 (0.01)	[0.20, 0.24]	< .001	.05
Emotion differentiation	−0.14 (0.01)	[−0.16, −0.13]	< .001	.08
Strategy × Emotion Differentiation	**−0.10 (0.01)**	**[−0.12, −0.09]**	**< .001**	**.01**
Lagged negative emotion	0.19 (0.02)	[0.16, 0.22]	.004	.05
Distraction				
Intercept	−0.01 (0.07)	[−0.14, 0.12]	.878	
Strategy	0.13 (0.02)	[0.09, 0.16]	.002	.01
Emotion differentiation	−0.14 (0.01)	[−0.16, −0.13]	< .001	.08
Strategy × Emotion Differentiation	**−0.05 (0.01)**	**[−0.07, −0.04]**	**< .001**	**.003**
Lagged negative emotion	0.22 (0.01)	[0.19, 0.25]	.001	.07
Cognitive reappraisal				
Intercept	−0.01 (0.07)	[−0.14, 0.12]	.883	
Strategy	0.11 (0.02)	[0.08, 0.15]	.010	.01
Emotion differentiation	−0.14 (0.01)	[−0.16, −0.13]	< .001	.08
Strategy × Emotion Differentiation	**−0.05 (0.01)**	**[−0.07, −0.03]**	**< .001**	**.003**
Lagged negative emotion	0.23 (0.01)	[0.20, 0.25]	< .001	.07
Expressive suppression				
Intercept	−0.01 (0.07)	[−0.15, 0.12]	.883	
Strategy	0.18 (0.01)	[0.15, 0.21]	< .001	.02
Emotion differentiation	−0.14 (0.01)	[−0.15, −0.13]	< .001	.08
Strategy × Emotion Differentiation	**−0.09 (0.01)**	**[−0.11, −0.07]**	**< .001**	**.01**
Lagged negative emotion	0.21 (0.01)	[0.18, 0.24]	.001	.06
Social sharing				
Intercept	−0.01 (0.07)	[−0.14, 0.12]	.881	
Strategy	0.09 (0.01)	[0.07, 0.11]	< .001	.004
Emotion differentiation	−0.14 (0.01)	[−0.16, −0.13]	< .001	.08
Strategy × Emotion Differentiation	**−0.06 (0.01)**	**[−0.08, −0.04]**	**< .001**	**.003**
Lagged negative emotion	0.23 (0.01)	[0.20, 0.25]	< .001	.07

Note: Boldface indicates significant effects in the variable of interest. Lagged negative emotion refers to negative emotion at the previous time point. CI = confidence interval.

low differentiators experience negative emotion, they 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 in the Supplemental Material.

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 (a) whether results replicated when putatively more complex (e.g., lonely) or less specific (e.g., stressed) emotion terms were included or omitted and (b) 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 (the sixth emotion was omitted). We ran both models across this multiverse of negative emotion and found that our results replicated across 100% of specifications. The details of these analyses are in the Supplemental Material (Figs. S1–S4). Finally, we replicated our analyses 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-related trends.

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, which

Table 4. Simple Slopes of Emotion-Regulation Strategies on Emotion at Low and High Levels of Emotion Differentiation in Study 1

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

Note: Degrees of freedom ($N - k - 1$) are 195. CI = confidence interval.

necessitate 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

The data used in this study were drawn from a larger study that received ethical approval from the KU Leuven Ethics Committee. We discuss the measures analyzed for only the current study. These data have not yet been used to test other research questions.

Participants. Participants were 101 Belgian first-year psychology students receiving results from their first semester (14 men; age: $M = 18.64$; $SD = 1.45$). Belgium has almost unrestricted access to universities; 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 an event with high personal relevance. Five first-year psychology subjects were offered, and most participants took all five ($n = 92$, or 91.1%). We aimed to recruit at least 100 students out of approximately 400 new enrollments, allowing us more than 80% power to detect medium-sized effects ($r = .30$, $\alpha = .05$). We recruited through a first-year research-participation session and through social media. All participants had more than 50% compliance, so no participants were omitted. Participants received €50 for completing at least 80% of the ESM and €5 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 were not given details about specific hypotheses. They then completed the ESM phase. On results-release day, within a 2-hr period, students were notified by e-mail 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.

For the 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 experience sampling: 2 days before the results release and 7 days after. We used a stratified random-interval scheme that sent a random signal within 10 equal intervals between 10:00 a.m. and 10:00 p.m. There was some variability in when results were released: Participants received their results between surveys 21 and 28 of 90. We were interested in regulation in response to results, and thus we included only postresults surveys, meaning that participants received between 63 and 70 surveys ($M = 68.69$). Participants received a signal on average every 71.9 min ($SD = 29.8$) 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 to the context of receiving learning outcomes (Pekrun, 2006). We kept "sad," "angry," "anxious," and "stressed" 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 "disappointed" and "ashamed" because of their centrality in retrospectively evaluating learning outcomes (Pekrun, 2006).

Negative-emotion differentiation. As in Study 1, we took the ICC between negative emotions within-person across measurement occasions, applied a Fisher's z transformation, and then reverse scored it so higher numbers equaled higher differentiation. There were no negative ICCs.

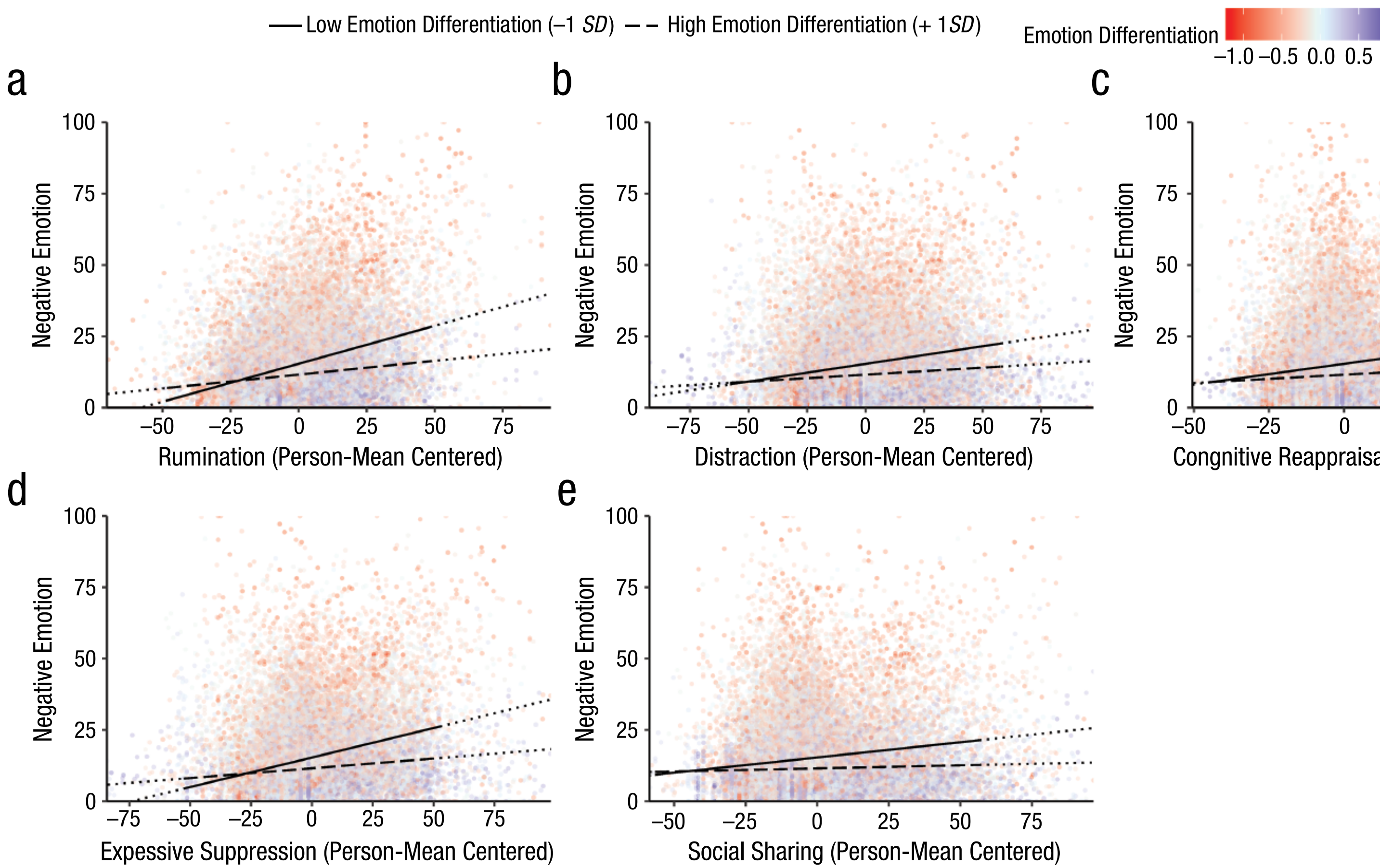

Fig. 1. Results from Study 1, Model 2: scatterplots showing the association between emotion-regulation strategy and level of emotion differentiation, separately for each of five strategies: (a) rumination, (b) distraction, (c) reappraisal, (d) suppression, and (e) sharing. Lines represent the simple slopes of low (–1 *SD*) and high (+1 *SD*) emotion differentiation. Analyses were conducted with standardized coefficients, but unstandardized coefficients are used here for interpretability (graphs using standardized coefficients are available in Fig. S9 in the Supplemental Material available online). Scatterplot points represent each momentary observation colored by person-level emotion differentiation (red = low differentiation, blue = high differentiation; note that emotion differentiation is Fisher's z transformed). Dotted lines are used when the estimated simple slopes are ±3 standard deviations from the mean of the predictor (emotion-regulation strategy) to represent the uncertainty in these estimates given relatively few observations. Emotion-regulation strategy is person-mean centered within wave, so we examined deviations around each individual's mean strategy intensity within that wave.

Emotion-regulation strategies. 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 passing grade and below 10 a failing grade. Failing requires retaking the exam later in the year or, in the case of too many failures, 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 grades using the same measure. We used this to compute an *expected-percentage-passed* variable. Including both expected and actual passing percentage, or the difference between actual and expected passing percentage, did not substantively change our results. Thus, we focus on actual passing 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 the emotional intensity of the stimulus. However, because we did not have the necessary statistical power, we did 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 included this variable in Model 1 to replicate Study 1.

Model 1: emotion differentiation as a predictor of emotion-regulation strategies. In Model 1, we used differentiation, percentage passed, and negative emotion, which were grand-mean centered, to predict each strategy separately (six models). We included random intercepts per participant.

Model 2: Emotion Differentiation × Emotion Regulation Strategies predicting negative emotion. In Model 2, we used differentiation, regulation, their cross-level interaction, and percentage passed to predict negative emotion (separately for each strategy; six models). We included 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 we 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 shown in Table 5, and within- and between-person correlations are shown in Table S3 in the Supplemental Material.

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

Model 2. As shown 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 was in contrast to Study 1, in which all strategies were associated with negative emotion. This result may be attributable to the fact that in Study 2, all measurement was linked to an event accounted for in analyses, thus better modeling the antecedents of regulation.

In line with Hypothesis 2, results showed interactions between differentiation and rumination, distraction, acceptance, and sharing (but not reappraisal or suppression). Table 8 shows the results of simple-slopes analyses, which are graphed in Figure 2. In line with Hypothesis 2a, results showed a positive association between rumination, distraction, and sharing and negative emotion for low differentiators. Partially supporting Hypothesis 2c, analyses showed no link for high differentiators between any strategy and negative

Table 5. Descriptive Statistics in Study 2

Variable	Mean	Within-person standard deviation	Between-person standard deviation	Intraclass correlation coefficient
Emotion differentiation	.37	—	.22	—
Percentage of exams 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: Intraclass correlation coefficients (ICCs) represent 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, we include the raw scores (i.e., without the Fisher's z transformation) for emotion differentiation, reverse scored.

emotion, but there was also no evidence for a negative link as proposed in 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%).

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 Supplemental Reverse Directional Analyses 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, differentiation and suppression in 66.7% of models, and differentiation and sharing in 50% of models. For Model 2, we found significant interactions between differentiation and rumination in 16.7% of models, differentiation and distraction in 83.3% of models, differentiation and acceptance in 100% of models, and differentiation and sharing in 100% of models. This suggests that the interaction with rumination was not robust across emotions included. For more detail, see Figures S5 through S8 in the Supplemental Material. Table 9 provides a summary of results across studies.

Discussion

It has been argued that differentiating between emotions provides information that could facilitate effective emotion regulation (Barrett & Gross, 2001). Given that 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 with selection.

Strategy selection

Contrary to Hypothesis 1, our results showed 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 in Study 2), and, as hypothesized, it was associated with reduced suppression and rumination in Study 2 (but not in Study 1). It may be that links between differentiation and maladaptive strategies emerge only within emotional events, in which 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. Recently, some researchers 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.

Table 6. Results From Model 1: Effects of Variables Predicting Emotion-Regulation Strategies in Study 2

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

Note: Boldface indicates significant effects in the variable of interest. Negative-emotion mean refers to the person mean of negative emotion. CI = confidence interval.

Strategy effectiveness

Supporting Hypothesis 2, our results revealed links between differentiation and effectiveness for all strategies in Study 1 and for four of six 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 the costs of nonacceptance rather than the benefits of acceptance. In high differentiators, we found an attenuated relationship between strategies and negative emotion. This result was consistent with the pattern predicted for maladaptive strategies in Hypothesis 2c; however, adaptive strategies were not associated with decreased negative emotion in high differentiators, contradicting Hypothesis 2b. 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 suggests 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 data sets, 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

Table 7. Results From Model 2: Effects of Variables Predicting Negative Emotion in Study 2

Strategy and predictor	Estimate (*SE*)	95% CI	*p*	Partial R^2
Rumination				
Intercept	< −0.001 (0.07)	[−0.15, 0.15]	.9996	
Strategy	0.08 (0.01)	[0.06, 0.11]	< .001	.01
Emotion differentiation	−0.02 (0.08)	[−0.17, 0.13]	.775	< .001
Percentage of exams passed	−0.58 (0.07)	[−0.73, −0.44]	< .001	.31
Strategy × Emotion Differentiation	**−0.02 (0.01)**	**[−0.05, −0.001]**	**.041**	**.001**
Lagged negative emotion	0.14 (0.01)	[0.12, 0.16]	< .001	.01
Distraction				
Intercept	−0.003 (0.07)	[−0.15, 0.14]	.967	
Strategy	0.02 (0.01)	[0.01, 0.04]	.018	< .001
Emotion differentiation	−0.04 (0.07)	[−0.18, 0.11]	.640	< .001
Percentage of exams passed	−0.57 (0.07)	[−0.72, −0.43]	< .001	.31
Strategy × Emotion Differentiation	**−0.03 (0.01)**	**[−0.04, −0.01]**	**.011**	**.001**
Lagged negative emotion	0.16 (0.01)	[0.14, 0.18]	< .001	.02
Cognitive reappraisal				
Intercept	−0.003 (0.07)	[−0.15, 0.14]	.965	
Strategy	0.02 (0.01)	[0.003, 0.04]	.026	.001
Emotion differentiation	−0.03 (0.07)	[−0.18, 0.12]	.692	< .001
Percentage of exams passed	−0.58 (0.07)	[−0.72, −0.43]	< .001	.31
Strategy × Emotion Differentiation	−0.02 (0.01)	[−0.04, 0.004]	.127	< .001
Lagged negative emotion	0.16 (0.01)	[0.14, 0.18]	< .001	.02
Acceptance				
Intercept	−0.004 (0.07)	[−0.15, 0.14]	.957	
Strategy	−0.04 (0.01)	[−0.06, −0.02]	.001	< .001
Emotion differentiation	−0.04 (0.07)	[−0.19, 0.10]	.553	< .001
Percentage of exams passed	−0.58 (0.07)	[−0.72, −0.43]	< .001	.31
Strategy × Emotion Differentiation	**0.03 (0.01)**	**[0.01, 0.05]**	**.003**	**.001**
Lagged negative emotion	0.16 (0.01)	[0.14, 0.18]	< .001	.02
Expressive suppression				
Intercept	−0.003 (0.07)	[−0.15, 0.14]	.969	
Strategy	0.04 (0.01)	[0.02, 0.06]	< .001	.002
Emotion differentiation	−0.03 (0.07)	[−0.18, 0.11]	.653	< .001
Percentage of exams passed	−0.58 (0.07)	[−0.73, −0.44]	< .001	.31
Strategy × Emotion Differentiation	−0.02 (0.01)	[−0.04, 0.002]	.092	< .001
Lagged negative emotion	0.16 (0.01)	[0.14, 0.18]	< .001	.02
Social sharing				
Intercept	−0.002 (0.07)	[-0.15, 0.14]	.977	
Strategy	0.04 (0.01)	[0.02, 0.05]	< .001	.001
Emotion differentiation	−0.03 (0.07)	[-0.18, 0.11]	.670	<.001
Percentage of exams passed	−0.59 (0.07)	[-0.73, -0.44]	< .001	.31
Strategy × Emotion Differentiation	**−0.03 (0.01)**	**[-0.05, -0.01]**	< **.001**	**.001**
Lagged negative emotion	0.16 (0.01)	[0.14, 0.18]	< .001	.02

Note: Boldface indicates significant effects in the variable of interest. Lagged negative emotion refers to negative emotion at the previous time point. CI = confidence interval.

small effect sizes will be important for follow-up work and interventions.

Implications and future directions

These studies are the first to consider several emotion-regulation strategies separately and to test multiple emotion-regulation 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 that theory, we found that it matters which part of the regulation process is considered. There were consistent links between differentiation and effectiveness, but not differentiation and selection, suggesting process-specific deficits.

Table 8. Simple Slopes of Emotion-Regulation Strategies on Emotion at Low and High Levels of Emotion Differentiation in Study 2

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

Note: Simple slopes were calculated only for significant interactions. Degrees of freedom ($N - k - 1$) are 95. CI = confidence interval.

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., 2019).

We did not test mechanisms, but we view such testing as an important next step. After analyzing prior research, we suggest four potential mechanisms. First, differentiation is associated with reduced overlap between emotional appraisals (Erbas, Ceulemans, Koval, & Kuppens, 2015). This suggests that 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), 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 our results in clinical samples. Second, because experience sampling necessitates brevity, we did not include all potential specific emotions. We selected items on the basis of 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 emotion 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—when low differentiators feel negative, they are more likely to use all strategies. We conducted reverse directional analyses that 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 the selection of emotion-regulation strategies but that low differentiation inhibited strategy effectiveness. Among low differentiators, emotion-regulation 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 emotion-regulation process and suggest the possibility of training emotion differentiation to address regulation difficulties.

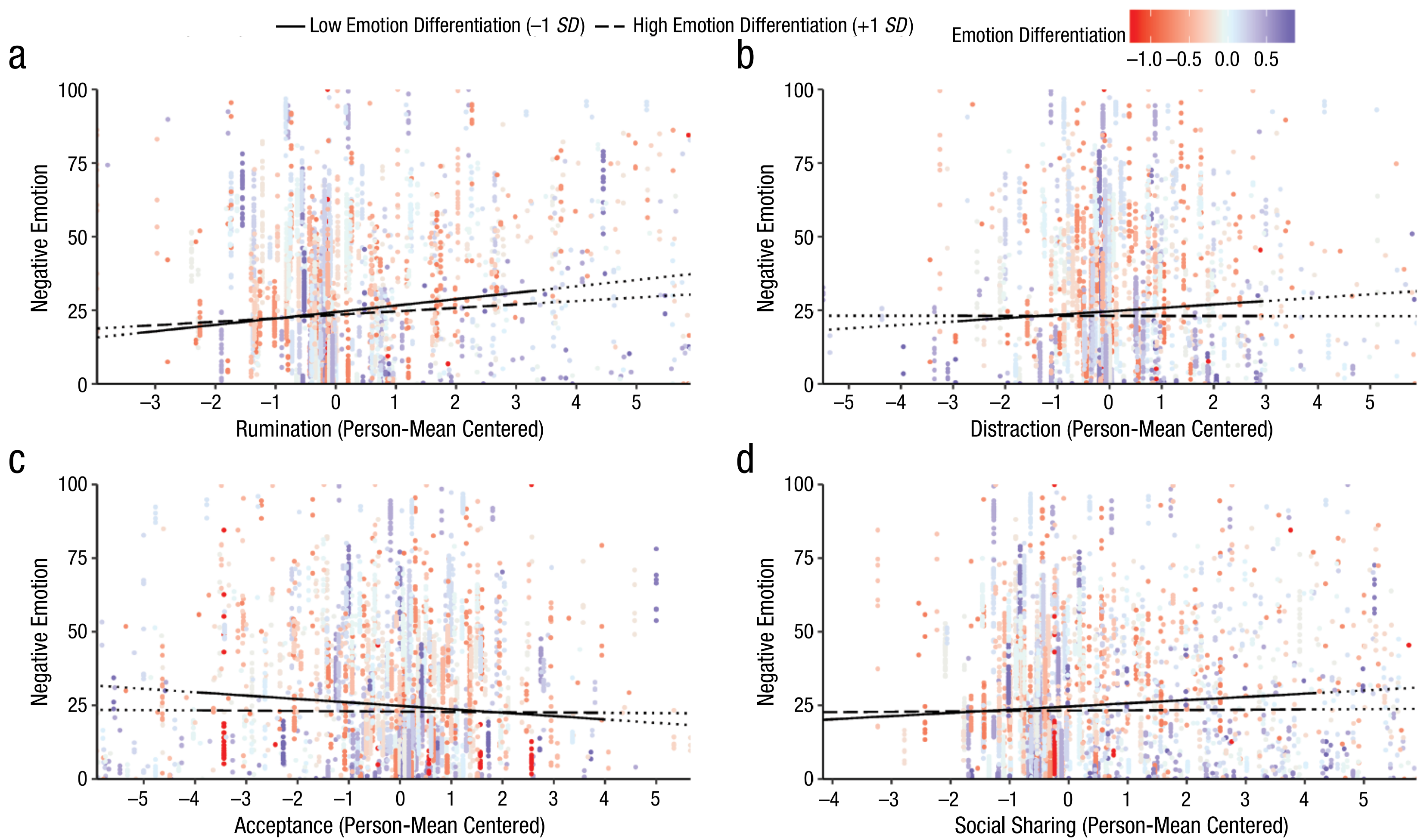

Fig. 2. Results from Study 2, Model 2: scatterplots showing the association between emotion-regulation strategy and level of emotion differentiation, separately for each of four strategies: (a) rumination, (b) distraction, (c) acceptance, and (d) sharing. Lines represent the simple slopes of low (–1 *SD*) and high (+1 *SD*) emotion differentiation. Analyses were conducted with standardized coefficients, but unstandardized coefficients are used here for interpretability (graphs using standardized coefficients are available in the Fig. S10 in the Supplemental Material available online). Scatterplot points represent each momentary observation colored by person-level emotion differentiation (red = low differentiation, blue = high differentiation; note that emotion differentiation is Fisher's *z* transformed). Dotted lines are used when the estimated simple slopes are ±3 standard deviations from the mean of the predictor (emotion-regulation strategy) to represent the uncertainty in these estimates given relatively few observations. Emotion-regulation strategy is person-mean centered, so we examined deviations around each individual's mean strategy intensity.

Table 9. Summary of Significant Strategy-Specific Associations With Emotion Differentiation Across Studies 1 and 2

Strategy	Hypothesis	Study 1 (N = 200; three waves)	Study 2 (N = 101; postexam 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 × 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

Note: Significance was defined as $p < .05$.

Action Editor

Michael Inzlicht served as action editor for this article.

Author Contributions

E. K. Kalokerinos and Y. Erbas share joint first authorship of this article. E. K. Kalokerinos and Y. Erbas developed the study concept with input from P. Kuppens and E. Ceulemans. The data were collected in part by E. K. Kalokerinos and Y. Erbas. E. K. Kalokerinos analyzed and interpreted the data with input from all authors. E. K. Kalokerinos and Y. Erbas drafted the manuscript, and P. Kuppens and E. Ceulemans provided critical revisions. All authors approved the final version of the manuscript.

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Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797619838763

Open Practices

The data, materials, code book, and analytic code used in these studies are available on the Open Science Framework at osf.io/bmaf2. The two studies reported in this manuscript were not formally preregistered. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797619838763. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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