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Modeling Individual Differences in Emotion Regulation Repertoire in Daily Life with Multilevel Latent Profile Analysis

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Abstract

Emotion regulation (ER) repertoire—the range of different ER strategies an individual utilizes across situations—is assumed to enable more adaptive ER and greater well-being. ER repertoire has been operationalized by a quantitative index (sum of ER strategies across situations) or by applying a person-centered approach to global self-reports of dispositional ER. We aimed to assess ER repertoire in daily life by using an experience sampling methodology (ESM) and a person-centered approach that could account for nested data. We used multilevel latent profile analyses of ESM data (*N* = 179, 9-10 prompts per day over 21 days) to (a) group the occasions into latent profiles of momentary ER strategies, (b) group individuals whose distributions of ER profiles differed across occasions into latent classes, and (c) examine well-being correlates of class membership at the person level. At the occasion level, we identified nine ER profiles that differed in degree of use (e.g., no use of any vs. strong use of all strategies) and in specific combinations of strategies (e.g., situation selection & acceptance vs. suppression & ignoring). At the person level, we identified five classes of individuals differing in the degree to which they used various momentary ER profiles versus one predominant profile across situations. Well-being was highest for individuals who used multiple ER profiles of active strategies and lowest for individuals who used ER profiles focused on suppression. Hence, both ER repertoire width and the specific make-up of the ER repertoire were relevant for the relation between ER repertoire and well-being.

Keywords: emotion regulation, emotion regulation repertoire, emotion regulation flexibility, multilevel latent profile analysis, person-centered analysis

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Individuals do not simply experience emotions, but they also evaluate them and attempt to shape the intensity, duration, and quality of their emotions (Gross, 2014). Research on emotion regulation (ER) has identified a wide variety of cognitive (e.g., distraction, reappraisal) and behavioral (e.g., seeking social support, substance use) strategies that individuals use to change or control their emotional states (e.g., Larsen & Prizmic, 2004). In recent years, there has been growing interest in individuals' ability to implement ER strategies that are synchronized with contextual demands—termed ER flexibility (Aldao, Sheppes, & Gross, 2015). According to Bonanno and Burton (2013), one component of ER flexibility is an individual's ER repertoire (i.e., the range of different ER strategies an individual utilizes across situations). As empirical studies have demonstrated, individuals differ in the size of their ER repertoire and the specific combination of ER strategies that make up their repertoire, and these individual differences have been shown to be related to individual differences in symptoms of psychopathology (e.g., De France & Hollenstein, 2017; Eftekhari, Zoellner, & Vigil, 2009; Lougheed & Hollenstein, 2012) and treatment outcomes in individuals being treated for alcohol use disorder (Roos & Witkiewitz, 2016). In general, rather than examining the adaptiveness of single ER strategies, one advantage of a multivariate approach to the study of ER is the potential to shed light on combined or interactive effects of ER strategies on psychosocial functioning (Aldao, 2013).

Previous research on ER repertoire has been limited in a number of respects. In studies examining ER strategy use in response to specific emotion-eliciting stimuli (e.g., Aldao & Nolen-Hoeksema, 2013; Quiñones-Camacho & Davis, 2018; Rao & Gibson, 2018), ER repertoire has been operationalized as a single quantitative index (e.g., the sum of unique ER strategies), which does not capture possible qualitative differences in the make-up of individuals' ER repertoires.

Other studies have applied a person-centered approach to studying ER repertoires (e.g., Dixon-Gordon, Aldao, & De Los Reyes, 2015; Lougheed & Hollenstein, 2012), which identifies different classes of individuals who use specific combinations (i.e., profiles) of ER strategies. However, a limitation of previous person-centered approaches to studying ER repertoires is that most have relied on global trait measures of dispositional ER strategy use. Given that global trait self-reports draw on people's recall and aggregation of their behavior and experiences over extended periods of time and across many situations rather than on their momentary behavior and experiences (Robinson & Clore, 2002), trait ER measures do not necessarily correspond with how people use ER strategies in daily life situations (e.g., Brockman, Ciarrochi, Parker, & Kashdan, 2017). Therefore, in the present research, our aim was to combine the advantages of the two previous approaches—that is, to examine profiles of momentary ER in response to emotional experiences and to identify classes of individuals who differ in their use of specific ER profiles across situations—by applying multilevel latent profile analysis (ML-LPA) to experience sampling method (ESM) data.

The Role of Strategy Repertoire in the ER Process

Successfully regulating emotions is a complex and multi-faceted task (e.g., Bonnano & Burton, 2013; Webb, Gallo, Miles, Gollwitzer, & Sheeran, 2012). Recognizing this, Gross's (2015) extended process model of ER distinguishes between three stages of ER: (a) identifying the emotions to be regulated, (b) selecting an ER strategy, and (c) implementing an ER strategy. It is primarily at the selection stage that an individual's ER repertoire—both the size of an individual's regulatory "toolbox" and the specific combination of "tools" that are available—may impact the success or failure of the ER process. According to Gross (2015), the selection stage includes an evaluation of potential ER strategies in light of current contextual factors (e.g., available cognitive resources) as well as specific characteristics of the perceived emotion (e.g., its intensity). To down-regulate mild anger, for instance, individuals might choose a different strategy (e.g., reappraisal) than they would choose to down-regulate intense anger (e.g., distraction; Sheppes et al., 2014). Hence, having many potential ER strategies from which to draw should help individuals tailor their regulatory behavior to the situational context. Conversely, ER may fail at the selection stage if a person has very few ER strategies to choose from (Gross, 2015).

Another reason why a broad ER repertoire should enhance the probability of successful ER in a given situation is that a large and diverse regulatory "toolbox" enables a person to use multiple ER strategies at the same time—a phenomenon that has recently been termed "emotion polyregulation" (Ford, Gross, & Gruber, 2019). Empirical studies on the spontaneous use of ER strategies have shown that people tend to implement various ER strategies simultaneously (or in close succession) when confronted with an emotion-eliciting stimulus. In their lab study, Aldao and Nolen-Hoeksema (2013) found that two thirds of participants who engaged in an effort to regulate their emotions reported using two or more ER strategies while viewing a disgust-inducing film clip. In an ESM study that assessed naturalistic regulatory responses to emotions (Heiy & Cheavens, 2014), participants reported using an average of seven different ER strategies to reduce the intensity of negative emotions within a single sampling period. In another ESM study, Brans et al. (2013) reported positive within-person correlations among all six ER strategies they assessed, suggesting that people tend to increase/decrease their use of multiple ER strategies simultaneously in daily life.

Measuring Individuals' ER Repertoire

Previous research on ER repertoire has adopted one of two empirical approaches to studying ER repertoire: In the first approach, participants are confronted with specific emotion-eliciting stimuli or situations and are requested to indicate which ER strategies they used (or would use) in response to these stimuli or situations, such as recalled emotional episodes (Quiñones-Camacho & Davis, 2018), emotional vignettes (Rao & Gibson, 2018), emotion-inducing films (Aldao & Nolen-Hoeksema, 2013), or emotions experienced in daily life (Eldesouky & English, 2018; Heiy & Cheavens, 2014). Participants' endorsement of ER strategies are then recoded into a binary indicator of whether each ER strategy was used to some degree versus not at all. Subsequently, this information is reduced to a single quantitative index, such as the sum of unique ER strategies reported across situations or occasions, representing ER repertoire. As a variant of this general approach, Quiñones-Camacho and Davis (2018) created emotion-specific repertoire scores (for the regulation of anger, fear, and sadness), and Eldesouky and English (2018) computed daily repertoire scores.

An advantage of this approach is that individuals' use of ER strategies is assessed in response to specific stimuli, events, or daily experiences, which may be particularly ecologically valid. A limitation of this approach, however, is that it is unclear how the results generalize to other contexts than the ones studied. Another limitation of this approach is that the available information is reduced to a single quantitative index for which all ER strategies are treated as interchangeable. Hence, analyses of whether the specific combination of ER strategies that are applied matter for adaptive psychosocial functioning are precluded.

The second approach that studies on ER repertoire have used is a person-centered approach. Studies that fall into this category differ in terms of the specific statistical model that they applied to analyze individuals' ratings of ER strategy: Some studies (e.g., Chesney & Gordon, 2017; Eftekhari et al., 2009) have used cluster analysis, whereas others (e.g., De France & Hollenstein, 2017; Dixon-Gordon et al., 2015; Lougheed & Hollenstein, 2012; Zalewski, Lengua, Wilson, Trancik, & Bazinet, 2011) have used latent class analysis (LCA) or latent profile analysis (LPA). These statistical methods share the goal of identifying clusters (classes) of individuals who show similar patterns of scores on several observed variables. LCA and LPA differ from traditional cluster analytic methods in that they are model based (i.e., make distributional assumptions for the observed indicators within classes), have more rigorous criteria for identifying the number of latent classes, and assign each individual to a latent class with a certain probability (e.g., Masyn, 2013). LCA is suitable for categorical observed variables, and LPA is suitable for continuous observed variables.

An advantage of a person-centered approach to studying ER repertoire is that it allows a holistic view of ER strategy use. Specifically, the profiles that emerge in a sample of participants can be interpreted both in terms of their width (e.g., moderate to high mean levels of only one or a few vs. several ER strategies) and in terms of the specific strategies that are predominantly used (e.g., propensity for suppression vs. engagement strategies). However, most studies adopting a person-centered approach have relied on global self-reports of dispositional ER strategy use. Thus, the latent classes identified in these studies represent types of individuals who differ in their judgments about which ER strategies they typically use. In general, global self-reports are assumed to tap semantic knowledge—that is, conceptual knowledge abstracted from time and place (Conner & Barrett, 2012). Hence, people’s reports of their habitual use of ER strategies may not necessarily correspond with their actual use of ER strategies in daily life (Brockman et al., 2017; Koval et al., 2018).

Empirical Relations between ER Repertoire and Well-Being Indices

Evidence for the relation between ER repertoire and well-being indicators has been mixed: In line with the hypothesis that a larger repertoire should be adaptive, Quiñones-Camacho and Davis (2018) found that a smaller anger regulation repertoire was related to more externalizing symptoms in children, although this relation did not generalize to sadness- or fear-regulation repertoires. Contrary to expectations, in the lab study by Aldao and Nolen-Hoeksema

(2013), participants who used multiple ER strategies during the disgust-eliciting film reported higher levels of disgust than participants who reported using only one strategy. Finally, Heiy and Cheavens (2014) found that the number of unique ER strategies participants reported using across situations in daily life was unrelated to their overall mood or neuroticism.

Of the studies that used a person-centered approach, a few found support for the view that a larger ER repertoire should be adaptive: Lougheed and Hollenstein (2012), for instance, found that adolescents with ER profiles indicating a limited range of strategies reported more internalizing problems (depressive and anxiety symptoms) than adolescents with ER profiles indicating a greater range. Similarly, Roos and Witkiewitz (2016) found that individuals being treated for alcohol use disorder who demonstrated a broader coping repertoire had better treatment outcomes. Other results have suggested that larger repertoires are not necessarily related to better outcomes and that, instead, the specific make-up of one's ER repertoire seems to be relevant: In the study by Eftekhari et al. (2009), a cluster of individuals characterized by high trait reappraisal and low trait suppression use consistently reported the least amount of general psychopathology compared with all other clusters. Likewise, in a community sample, Chesney and Gordon (2017) found that a cluster of individuals who reported habitually using ER strategies traditionally seen as "maladaptive" (avoidance, suppression, and rumination) showed more severe posttraumatic stress symptoms than a cluster characterized by ER strategies traditionally seen as "adaptive" (problem solving, acceptance, and reappraisal). Finally, De France and Hollenstein (2017) reported that individuals with an "Engagement Propensity" profile (with high levels of emotion expression) did not differ from individuals who used six different ER strategies to an average degree ("Average" profile) in terms of psychosocial functioning, but individuals with a "Suppression Propensity" profile reported higher anxiety, depression, and social anxiety (but also higher relationship quality) than individuals with an "Average" profile. Taken together, ER repertoire appears to play an important role in the ER process and there is some empirical evidence that individual differences in the size and specific composition of people's ER repertoire relates to their psychological functioning and well-being.

Aims of the Present Research

The present research builds on and extends existing research on ER repertoire by combining the advantages of two previous approaches: To avoid the shortcomings of global self-reports of dispositional ER and to enhance ecological validity, we studied the momentary use of ER strategies in daily life via ESM. Moreover, to gain information about both the size (i.e., number of ER strategies used) and specific composition (i.e., propensity to use specific ER strategies) of individuals' ER repertoire, we applied a person-centered approach to the ESM data. ESM reports of momentary ER strategy use yields nested data (measurement occasions nested within persons). To statistically model specific combinations (profiles) of momentary ER strategies and to simultaneously account for individual differences in the use of profiles of momentary ER strategies across occasions, we applied an extension of LPA—multilevel LPA (ML-LPA; Vermunt, 2003). To date, multilevel latent class analytic models (multilevel LCA for categorical observed variables and ML-LPA for continuous observed variables) have mainly been applied to cross-sectional nested data sets such as students nested in schools (e.g., Van Eck, Johnson, Bettencourt, & Johnson, 2017) or employees nested in work departments (e.g., Mäkikangas et al., 2018). In the present research, we applied ML-LPA to ESM data in order to (a) group measurement occasions (at the within-person level) into latent profiles of momentary ER strategies, (b) group individuals (at the between-person level) into latent classes of individuals who differ in their distributions of latent ER profiles across occasions, and (c) analyze mean differences in well-being between the latent classes of individuals at the between-person level.

In particular, we addressed the following research questions and hypotheses: First, given the lack of studies on profiles of momentary ER in daily life, we asked: Which ER strategies are typically used in conjunction in daily life (i.e., How many profiles of momentary ER strategies can be distinguished and what characterizes them)? Second, on the basis of theoretical accounts of the role of ER repertoire in the ER process (e.g., Bonnano & Burton, 2013; Gross, 2015), we expected that individuals would differ in their use of ER profiles over time (e.g., a class of individuals using diverse sets of ER over time vs. a class of individuals using the same ER profile over and over again). Furthermore, we predicted that individuals with a larger/more diverse repertoire of ER strategies would show higher scores on dispositional well-being indicators.

As covariates of ER repertoire, previous studies have focused primarily on symptoms of psychopathology such as depression, anxiety, and stress (e.g., Lougheed & Hollenstein, 2012; Quiñones-Camacho & Davis, 2018), disordered eating and borderline personality (Dixon-Gordon et al., 2015), or posttraumatic stress (Chesney & Gordon, 2017). To our knowledge, positively poled indicators of well-being such as pleasant affect and life satisfaction have not yet been examined as potential correlates of individual differences in ER repertoire. Therefore, in addition to examining indicators of well-being deficits (i.e., depression, anxiety, stress, and unpleasant affect) for comparability with previous findings, we also examined life satisfaction and pleasant affect as positive poled indicators of well-being (Diener, 2000).

Method

Participants

One hundred and eighty-six participants were recruited by responding to advertisements distributed across traditional (e.g., printed flyers) and digital (e.g., social media and classifieds websites) media platforms. To be eligible, participants had to (i) be aged 18+ years, (ii) own a compatible iOS or Android smartphone for the ESM app, (iii) be fluent in English, (iv) have access to a computer running a recent version of Windows or Mac OS, and (v) not be currently taking heart or blood pressure medication. The last two inclusion criteria were necessary for another part of the study involving ambulatory physiology monitoring (not reported here). Prior to attending an initial lab session, participants were screened via a phone call to ensure they were eligible to participate. At the initial lab session, one participant was found ineligible and was excluded, and six others withdrew from the study during the EMA period, leaving a final sample of 179 adults (65% women) aged between 18 and 69 years (M = 27.02, SD = 8.98).

Procedure

The study comprised an initial lab session, an ESM period of 21 days, and a follow-up lab session. During the initial lab session, participants provided informed consent and completed a demographic questionnaire and several trait self-report measures. Participants were instructed to download *SEMA2*, a purpose-built smartphone application for ESM research (Harrison, Harrison, Koval, Gleeson, & Alvarez-Jimenez, 2017), onto their smartphones and received detailed instructions about the ESM procedure. SEMA2 was programmed to deliver ESM surveys each day between 10 a.m. and 10 p.m. at intervals of 80 +/- 30 minutes, resulting in approximately nine surveys per day. ESM surveys expired after 20 minutes to prevent back-filling. Participants were encouraged to complete as many ESM surveys as possible, however the researcher emphasized that answering surveys honestly and carefully was more important than completing all surveys. Prior to leaving the lab, participants completed a “demo” ESM survey with the researcher present and were encouraged to ask clarification questions. During the following 21 days, researchers emailed participants with weekly updates on their ESM compliance and to maintain participants’ engagement in the study. After 21 days, participants returned to the lab for a follow-up session, in which they completed several trait self-report measures again. Participants were reimbursed up to AU$150, partially contingent upon their ESM compliance. Ethical approval for the original study was obtained from the Australian Catholic University Human Research Ethics Committee.

Compliance with the ESM Protocol and Data Cleaning

On average, participants responded to 83.95% of the scheduled prompts (*SD* = 12.69%, Range = 34.87% to 100%).[1] A total of 29,956 measurement occasions were completed. To screen for careless responses, responses to individual items made in 500 ms or less (*n* = 4,969 items, 0.6%) were treated as missing. This resulted in missing values on all ER items for some of the occasions (*n* = 229 occasions, 0.7%), which were excluded from the present analyses. We also entirely excluded occasions in which 15 items or more were answered within 500 ms or less (*n* = 51 occasions, 0.1%) or in which responses to ESM items were made in less than 1,001 ms, on average (*n* = 180 occasions, 0.6%).

Due to technical errors, some prompts were delivered at incorrect intervals (too soon or too long after the previous signal). To ensure that the intervals between the prompts were within the intended range of 80 min +/- 30 min, these erroneous measurement occasions (*n* = 65 occasions, 0.2%) were excluded from the analyses. Therefore, the final sample that was analyzed in the present study comprised 29,431 measurement occasions nested in 179 participants[2].

Measures

[1] Three participants had ESM compliance rates below 50%, often used as a threshold for excluding participants from analyses in ESM studies. To ensure that our results were robust, we re-ran our main analyses excluding data from these participants and obtained very similar findings supporting identical substantive conclusions. We therefore report results of analyses using the full sample (*N* = 179).

[2] Sample size considerations during the study planning phase were done on the basis of multi-level modeling (addressing research questions which are not part of the current study). In this context, statistical power is more influenced by the number of persons (upperlevel units) than the number of assessments (Bolger & Laurenceau, 2013). At the person-level, to detect effect sizes of at least *r* = .25, with an alpha-level of .01 and a power of .80, requires a sample size of approximately *n* = 180. In the context of multilevel latent class-analytic approaches, which were applied in the present study, class separation and the number of indicators have been shown to have a strong impact on the power to detect the correct number of latent classes on the two levels, with higher separation between classes and a larger number of indicators yielding higher power (Park & Yu, 2018). For BIC(n_{Level2}) as a model fit criterion, Lukociene et al. (2010) showed that across different degrees of class separation and across different Level-2 sample sizes, a sample size of 50 Level-1 units per Level-2 unit yielded a very high percentage of simulation replications, in which the number of lower- and higher-level classes is correctly estimated (> 96%). For a sample size of 100 units on Level 2 (across different Level-1 sample sizes and different degrees of class separation), in 89% (74%) of simulation replications, the number of Level-1 (Level-2) classes was correctly estimated. In the present study (with 179 individuals at Level 2 and more than 150 occasions per individual at Level 1), these sample sizes were exceeded, and hence, we deemed our dataset large enough to apply ML-LPA models.

Momentary ER. At each ESM prompt, participants reported how often they had used each of ten ER strategies "since the last survey" on a response scale that ranged from 0 (*not at all*) to 100 (*very much*). Eight of these ER strategies were included to capture all stages of Gross's (2014; 2015) process model of ER, namely *situation selection* ("I chose which situation to put myself in"), *situation modification* ("I actively changed something in the situation"), *attentional deployment* (i.e., distraction: "I did something to distract myself physically or mentally"; and rumination "I thought over and over again about my emotions"), *cognitive change* (i.e., reappraisal-change: "I changed the way I was thinking about the situation"; and reappraisal-perspective: "I took a step back and looked at things from a different perspective") and *response modulation* (i.e., suppression: "I was careful not to express my emotions to others"; and social sharing: "I talked with someone about my emotions"). In addition, we assessed two other ER strategies that have been frequently studied, but are not easily categorized within Gross's process model, namely acceptance ("I accepted my emotions as valid and important") and ignoring ("I ignored my emotions"). Because the two cognitive change strategies both assessed forms of cognitive reappraisal and were moderately correlated (within-persons r = .42) and to minimize redundancy, we formed a composite momentary reappraisal score by calculating the mean of these two items. Hence, the overall number of different ER strategies was reduced to nine.

Well-being measures. Well-being was measured with global self-reports of life satisfaction, depression, anxiety, and stress at two measurement occasions (t1: initial lab session and t2: follow-up session). As indicators of dispositional well-being, we formed aggregated scores of each well-being measure by taking the mean of the two self-reports across t1 and t2. In addition, indicators of dispositional pleasant affect and dispositional unpleasant affect were formed on the basis of measures of momentary pleasant and unpleasant affect assessed during the

ESM phase of the study. As an indicator of reliability, we calculated omega for all well-being measures (Dunn, Baguley, & Brunsden, 2014).

Life satisfaction. Life satisfaction was measured with the five-item Satisfaction with Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985). An example item is “In most ways my life is close to my ideal.” Items are scored on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). At t1 and t2, Omega was .90. The t1 and t2 scores were averaged to form an indicator of dispositional life satisfaction.

Depression, anxiety and stress. The well-being measures also included the 21-item short form of the Depression Anxiety Stress Scales (DASS-21; Henry & Crawford, 2005), which assesses the frequency and severity of symptoms over the past week (*depression*: “I felt downhearted and blue”; *anxiety*: “I felt I was close to panic”; and *stress*: “I found it hard to wind down”) on a scale ranging from 0 (*did not apply to me at all*) to 3 (*applied to me very much or most of the time*). For the depression scale, omega was .88 at t1 and .87 at t2; for the anxiety scale, omega was .68 at t1 and .78 at t2; and for the stress scale, omega was .83 at t1 and .82 at t2. For each subscale, the t1 and t2 scores were averaged to form indicators of dispositional depression, anxiety, and stress.

Pleasant and unpleasant affect. At each ESM prompt, participants indicated how happy, relaxed, confident, sad, stressed, and angry they felt in the moment when the signal came, using a scale ranging from 0 (*not at all*) to 100 (*very much*). Momentary pleasant and unpleasant affect scores were computed by averaging the pleasant affect items (happy, relaxed, confident) and the unpleasant affect items (sad, stressed, angry), respectively. Next, momentary pleasant and unpleasant affect scores were aggregated across all measurement occasions to obtain mean scores for each participant across the 21-day ESM phase. The scales’ reliabilities on the person level were estimated by applying the method presented by Geldhof, Preacher, and Zyphur (2014). The between-persons Omega was .93 for pleasant affect and .89 for unpleasant affect.

Analytic Strategy

Series of ML-LPAs were conducted using Latent Gold 5.1 (Vermunt & Magidson, 2016) to identify latent profiles (i.e., configurations) of ER strategies used in daily life at the occasion level (Level 1) and to differentiate between latent classes of individuals at the person level (Level 2) who differ in their use of ER profiles over time. That is, we applied a nonparametric variant of the ML-LPA model in which differences across Level 2 units (in our case, individuals) are modeled using a discrete latent variable at Level 2 (Vermunt, 2003). The person-level classes represent individual differences in the distribution of the occasion-level ER profiles (i.e., differences between individuals in the probability with which they use different ER profiles in daily life). The nine ER strategies were entered as observed continuous variables, and a person identifier variable was entered as the grouping variable for the multilevel structure. All models were estimated by using 500 sets of random starting values to avoid local maxima (e.g., Masyn, 2013).

To identify the optimal model with an adequate number of latent profiles/classes at both levels, we followed the three steps recommended by Lukočienė, Varriale, and Vermunt (2010): First, we conducted a series of LPAs (ignoring the multilevel structure) to determine the optimal number of profiles at Level 1 (i.e., profiles of momentary ER at the occasion level). Second, we specified ML-LPA models and fixed the number of Level 1 profiles to the value of the first step and determined the number of Level 2 (person-level) classes. Third, we re-evaluated the number of Level 1 (occasion-level) profiles by fixing the number of person-level classes to the value of the second step. The aim of the third step was to evaluate whether the number of Level 1 profiles changed after accounting for the multilevel data structure.

We used the following criteria to determine the number of profiles/classes (Lukočienė et al., 2010): We compared the models' goodness of fit using the Bayesian information criterion (BIC; Schwarz, 1978) and the Akaike information criterion 3 (AIC3; Bozdogan, 1987). When using the BIC in the context of multilevel analysis, either the number of Level 1 units (occasions) or the number of Level 2 units (individuals) can be used as the sample size. As the simulation studies by Lukočienė et al. (2010) demonstrated, to decide how many profiles/classes should be modelled at both levels, the BIC based on the Level 2 sample size performed better than the BIC based on the Level 1 sample size. Therefore, we used the BIC(n_{Level2}) as a goodness-of-fit criterion in the present study. Information criteria values may continue decreasing as the number of latent profiles/classes increases even though these classes are not meaningfully different and might not represent distinct groups (e.g., Masyn, 2013). Thus, we additionally examined the size of the decrease in the BIC and AIC3 and explored whether the decrease flattened out at some point (Nylund, Asparouhov, & Muthén, 2007). As additional model selection criteria, we used the quality of latent profile/class separation (entropy R-squared, classification error, and the average posterior class probability) and the substantive interpretability of the profile solution (e.g., Masyn, 2013; Marsh, Lüdtke, Trautwein, & Morin, 2009). With respect to interpretability, the more parsimonious solution should be selected if an additional class in a *k* class model represents only a slight variation of a class found in a *k*–1 class model (e.g., Hadiwijaya, Klimstra, Vermunt, Branje, & Meeus, 2015).

For the final model, we analyzed whether the person-level classes differed in mean levels of well-being measures. For the mean comparisons across person-level classes, we applied the adjusted three-step approach (Bakk, Tekle, & Vermunt, 2013) implemented in Latent Gold 5.1. This method allowed us to use class membership as a predictor of the covariates while accounting for classification error in class assignment. The statistical significance of the mean differences in covariates across classes was evaluated with Wald tests. As a standardized effect size measure for the mean differences across classes of individuals, we calculated η^2.

Results

Descriptive Statistics

Descriptive statistics for the ER strategies can be found in Table 1. Descriptive statistics for the well-being measures can be found in Table 2.

Multilevel Latent Profile Analyses of ER Strategies

To identify the optimal ML-LPA model with an adequate number of latent profiles/classes at both levels, the first step was to determine the number of ER profiles at Level 1 (the occasion level). Table 3 shows the fit coefficients for a series of LPA models (i.e., ignoring the multilevel structure) with up to 11 profiles. The BIC and AIC3 continued to decrease as model complexity increased. Among the solutions with more than four profiles, the nine-profile solution showed the largest drops in the BIC and AIC3, the highest entropy R-squared value, the lowest classification error, and the highest average posterior class probability. Compared with the four-profile solution, which performed similarly in terms of class separation indices (classification error and average posterior class probability), the nine-profile solution clearly added qualitatively distinct ER profiles and not just minor variations of profiles found in the four-profile solution. Compared with the nine-profile solution, the 10-profile solution did not add a qualitatively distinct ER profile. Hence, nine profiles were selected at Level 1 in the first step.

In the second step, we determined the number of Level 2 classes (i.e., classes of individuals differing in their distributions of occasion-level ER profiles over time). Table 4 shows the fit coefficients for a series of ML-LPA models with nine Level 1 profiles and one to seven Level 2 classes. Again, the BIC and AIC3 continued to decrease as model complexity increased. The models with nine occasion-level profiles and either four, five, or six person-level classes were the best-fitting models in terms of the other model selection criteria, but no single model performed best on all criteria. In terms of substantive interpretability, the models with five and six person-level classes added a qualitatively distinct class compared with the model with one class less. Therefore, we compared the five- and six-class solutions by testing whether they could be cross-validated across two subsamples. We randomly split the sample of Level 1 units (measurement occasions) into two subsamples and estimated the two ML-LPA models in each subsample. The model with nine occasion-level profiles and five person-level classes was replicated across subsamples, whereas the model with nine occasion-level profiles and six person-level classes did not replicate across subsamples. Therefore, we selected five person-level classes at Level 2.

In the third step, we re-evaluated the number of Level 1 profiles by comparing models with five person-level (Level 2) classes and different numbers of occasion-level (Level 1) profiles. Table 5 shows the fit coefficients for a series of ML-LPA models with five Level 2 classes and up to 11 profiles at Level 1. The BIC and AIC3 again continued to decrease as model complexity increased. With respect to the quality of classification at Level 1 (entropy R-squared, classification error, and average posterior class probability on Level 1), the model with nine Level 1 profiles again emerged as the best. Hence, the model with nine occasion-level ER profiles and five person-level classes was selected as the final model.

Interpretation of Profiles of Momentary ER and Person-Level Classes

Figure 1a displays the conditional means for each ER strategy for the nine profiles in the original metric. In addition, Figure 1b shows the configurations of ER strategies as standard deviations from the overall sample mean to aid the interpretation of each profile's characteristics. The profiles are ordered by size (i.e., the number of occasions that were assigned to this profile). Among the nine ER profiles were three profiles that were relatively uniform across ER strategies and differed mainly in level. Accordingly, we labeled them the “multi-ER (moderate level)” profile (P1), “multi-ER (high level)” profile (P8), and “no ER” profile (P4). The six other profiles differed qualitatively and were characterized by a specific combination of a small number of ER strategies: the “situation selection & acceptance” profile (P2), the “situation modification” profile (P3), the “social sharing & situation modification” profile (P5), the “suppression & situation modification” profile (P6), the “suppression & ignoring” profile (P7), and finally the “social sharing” profile (P9).

Figure 2 shows the distribution of occasion-level ER profiles over time for the five classes of individuals. Three classes of individuals were characterized by the frequent use of only one particular ER profile over time (and the infrequent use of the other ER profiles): the “predominantly no ER profile” class (C4) used the “no ER” profile (P4) on 70% of all measurement occasions, the “predominantly multi-ER (high level) profile” class (C5) used the “multi-ER (high level)” profile (P8) on 73% of all measurement occasions, and the “predominantly multi-ER (moderate level) profile” class (C3) used the “multi-ER (moderate level)” profile (P1) on 67% of all measurement occasions. Two classes of individuals showed a more diverse use of momentary ER profiles over time, with a qualitatively different focus: Class C1 relied on ER profiles that were characterized by situation selection and acceptance (P2), situation modification (P3), and social sharing (P5, P9). Hence, we labeled C1 the “diversity of profiles (active regulation focus)” class. At more than 40% of all measurement occasions, Class C2 used ER profiles that contained suppression as a main ER strategy (P6, P7) and, hence, was labeled “diversity of profiles (suppression focus)” class.

Differences between Classes of Individuals in Well-Being

To test our hypotheses that individuals who demonstrate a larger/more diverse repertoire of ER strategies show higher dispositional well-being, we analyzed whether the mean values of the well-being measures differed across classes of individuals. Means and standard deviations of the well-being measures for the different classes of individuals are displayed in Table 6. Standardized effect sizes for overall mean differences across classes were small for life satisfaction, depression, and stress, medium for anxiety, and large for pleasant and unpleasant affect (see second last row in Table 6). Wald tests, shown in the last row of Table 6, revealed that mean differences in life satisfaction and depression were not statistically significant at $p < .05$ ($p = .052$ for life satisfaction and $p = .054$ for depression). However, the latent classes differed significantly in pleasant affect ($p < .001$), unpleasant affect ($p < .001$), anxiety ($p < .01$), and stress ($p < .05$). We therefore conducted pairwise comparisons between classes on these four well-being measures, which revealed that the diversity of profiles (active regulation focus) class (C2) had more pleasant affect, lower unpleasant affect, lower anxiety, and lower stress than the diversity of profiles (suppression focus) class (C1). For anxiety and stress, the other classes with a predominant multi-ER or no-ER profile (C3 to C5) fell between classes C1 and C2. As an exception to this, the predominantly multi-ER (high level) profile class (C5) experienced the most pleasant affect, and the predominantly no ER profile class (C4) did not differ from the diversity of profiles (active regulation focus) class (C2) in unpleasant affect.

Discussion

The current study is the first, to our knowledge, to apply ML-LPA to model individual differences in profiles of momentary ER strategy use in daily life. This approach enabled us to simultaneously describe momentary patterns of ER strategy co-occurrence (at the occasion level) and individuals' tendency to engage specific profiles of momentary ER strategies over time (at the person level). Building on previous research, we examined both the size and specific composition of individuals' ER repertoires in daily life.

At the occasion level, we identified nine latent ER profiles. Three of these ER profiles were relatively uniform and differed mainly in level (i.e., no ER strategies vs. all strategies used to a moderate degree vs. all strategies used to a strong degree). The other six ER profiles differed qualitatively with respect to the specific combination of ER strategies used. Interestingly, most of the profiles of momentary ER strategies reflected the use of multiple ER strategies at one occasion. This finding is in line with previous ESM studies reporting that individuals typically deploy multiple ER strategies concurrently (or in close succession) to regulate emotional experiences in daily life (Brans et al., 2013; Heiy & Cheavens, 2014). This also highlights the importance of assessing multiple strategies at a single occasion as opposed to assuming that individuals use only a single ER strategy to regulate emotions in a particular situation (cf. Ehring, Tuschen-Caffier, Schnülle, Fischer, & Gross, 2010).

At the person level, we identified five latent classes of individuals. Three classes were characterized by very low diversity in ER profile use across situations (i.e., ESM occasions). Individuals in these low-diversity ER classes tended to predominantly use one of the three uniform ER profiles (i.e., no use of any ER strategies, moderate use of almost all ER strategies, or intense use of almost all ER strategies). In a similar vein, previous person-centered analyses of dispositional ER have revealed subgroups of individuals who reported generally using no (or almost no) ER strategies (e.g., the “low regulators” cluster identified by Eftekhari et al., 2009) or almost all ER strategies to an “average” degree (e.g., the “average strategy use” profiles identified by De France & Hollenstein, 2017 and Lougheed & Hollenstein, 2012). Two out of the five latent classes of individuals in our study showed a more diverse use of ER profiles across occasions but each with a qualitatively different focus: Individuals in one of these classes employed various ER profiles that included “active” ER strategies, among which situation modification, situation selection, and social sharing were the predominant strategies. In contrast, individuals in C1 deployed ER profiles with a suppression focus on nearly half of all ESM occasions. An ER profile that is characterized by a propensity to suppress or conceal emotional responses has also been reported in studies on dispositional ER (e.g., Lougheed & Hollenstein, 2012; Zalewski et al., 2011) as well as an ER profile with a more active regulation focus (e.g., Chesney & Gordon, 2017; De France & Hollenstein, 2017). Compared with previous studies, however, the class with a propensity to use suppression-focused profiles over time in our study comprised more individuals (29%) than similar classes of individuals reported in previous research. For example, a suppression-propensity class was found to constitute only 3% of the sample by Lougheed and Hollenstein (2012) and 11% by Zalewski et al. (2011). One reason for the difference might be the age of the sample (adolescents/preadolescents vs. adults). Another reason might be the assessment method: Given that the studies by Lougheed and Hollenstein (2012) and Zalewski et al. (2011) relied on global self-reports of dispositional ER, one might speculate that participants underestimate their suppression-focused strategy use when completing global measures in comparison with the repeated measures of momentary ER captured in the current study. An underestimation of suppression in global reports might occur, for instance, due to perceived cultural norms around the expression of emotions (Matsumoto et al., 2008). As expected, the identified classes of individuals in our study differed in their level of dispositional well-being (as indicated by pleasant and unpleasant affect, anxiety, and stress). However, the width hypothesis, which states that an ER repertoire characterized by the use of more strategies over time should be related to higher well-being—regardless of the qualitative make-up of the repertoire—was not supported. Instead, the specific combination of ER strategies that individuals used over time (i.e., the content and not just the size of the “toolbox”) was relevant for dispositional well-being: We found higher pleasant affect, lower unpleasant affect, and fewer anxiety and stress symptoms among individuals in the “diversity of profiles (active regulation focus)" class relative to the "diversity of profiles (suppression focus)" class. Similarly, in previous person-centered analyses, ER profiles that indicated a propensity for suppression were associated with more symptoms of psychopathology (e.g., De France & Hollenstein, 2017; Eftekhari et al., 2009; Lougheed & Hollenstein, 2012). Our findings are also consistent with evidence from ESM studies on daily suppression, which have revealed that greater daily suppression was related to negative intrapersonal consequences, including more depressed mood, more fatigue, lower self-esteem, and lower life satisfaction on a daily basis as well as increases in depressed mood over three months (Cameron & Overall, 2018).

Finally, our findings shed more light on the question of whether implementing a large range of ER strategies in response to an emotional event might be indicative of "haphazard and misguided attempts at regulation" (Aldao & Nolen-Hoeksema, 2013, p. 758). In Aldao and Nolen-Hoeksema's (2013) study, participants who used multiple ER strategies during a disgust-eliciting film reported higher levels of disgust than participants who reported using only one strategy. In our study, however, individuals who predominantly used a uniform ER profile of multiple, strongly endorsed ER strategies (C5) demonstrated the most pleasant affect over time. That is, our results show that using multiple strategies simultaneously (or in close succession) may be adaptive for (affective) well-being. A major difference between the studies is that the study by Aldao and Nolen-Hoeksema (2013) confronted participants with an emotion-eliciting film in the laboratory, where opportunities to modify the situation are more constrained than they are in daily life situations. Taken together, our results imply that it is not the width of the ER repertoire but rather the specific types of ER profiles that are used over time (even if one profile is predominant) that play an important role in successful regulation. Methodologically, this finding underscores the importance of using a person-centered approach to analyze ER repertoire instead of a single quantitative index.

Limitations and Future Directions

Several limitations of the current study should be noted. First, the design of the study did not allow us to distinguish between simultaneous and sequential implementation of ER strategies. Because participants were instructed to indicate the extent to which they had engaged in a specific ER strategy “since the last survey,” they could in principle have been referring to one or more emotional episodes during this time frame. The time between prompts was relatively short, but even in the case of a single emotion-eliciting situation, the use of multiple ER strategies might be sequential rather than simultaneous, and even the specific order in which multiple ER strategies are deployed may result in different emotional consequences (Peuters, Kalokineros, Pe, & Kuppens, 2019). Future research on the temporal aspects of ER strategy implementation is warranted.

Second, the design of the study did not allow us to separate attempts to use particular ER strategies from the degree to which these ER strategies were successfully implemented (i.e., translated into situation-specific tactics). According to the extended process model of ER (Gross, 2015), the size and the specific make-up of an individual’s ER repertoire should primarily impact the success or failure of the ER process at the selection stage. Nonetheless, to get a complete picture, future research might benefit from investigating the interaction between individuals’ ER repertoire and their ability to successfully implement ER strategies in given situations (cf. Ford, Karnilowicz, & Mauss, 2017; McRae, 2013).

Third, we were not able to examine emotion-specific use of ER strategies in the current study, as participants reported their use of ER strategies “since the last survey” without reference to a particular emotion or emotion-eliciting situation. However, previous research suggests that profiles of momentary ER strategies may differ across discrete emotions such as anger, fear, or sadness (e.g., Quiñones-Camacho & Davis, 2018). Future ESM studies might account for emotion-specificity in ER profiles by using event-contingent sampling of specific types of emotional events (e.g., situations that elicit anger vs. situations that elicit sadness).

Fourth, individual differences in response styles might account to some extent for individual differences in the distribution of ER profiles over time. As ER strategies were assessed using continuous slider scales, particularly the predominant use of a uniform ER profile over time (e.g., multiple, strongly endorsed ER strategies in class C5) may reflect a particular response style (e.g., extreme responding) as well as actual ER strategy use (cf. Baird, Lucas, & Donellan, 2017). Future research should include measures of response style to investigate the role they play in measures of ER repertoire. However, it should be noted that response styles may similarly play a role in univariate approaches (e.g., analysis of a particular ER strategy such as reappraisal); they may simply be less visible in these types of analyses as compared to our latent profile analysis approach.

Fifth, while the use of ESM maximizes the ecological validity of our findings, this comes at the cost of not being able to control the emotion-eliciting situations that individuals encounter in their daily lives. As a result, we cannot rule out the possibility that variability in the situational contexts people encounter in their daily lives contributes to individual differences in ER repertoires. Future research on ER repertoire might profit from combining ecologically valid ESM approaches to ER with a laboratory-based assessment of ER strategy use across multiple (controlled) situations.

Sixth, we followed guidelines (Lukočienė et al., 2010) to identify the optimal ML-LPA model with an adequate number of latent profiles/classes at the occasion level and the person level. In LCA/LPA applications, however, it is not unusual that the model selection criteria (information criteria and class separation indices) do not clearly favor a single model, but that instead, two (or more) models perform equally well (Masyn, 2013). This was also the case in the present study. Hence, to decide between candidate models, we evaluated whether the k class model added a qualitatively distinct class (compared with the k-1 class model). This strategy has been suggested as an additional—albeit to some degree subjective—model selection criterion in the literature (for a discussion, see e.g., Marsh et al., 2009). To gain more confidence in the multilevel latent profile/class solution, we used a split-sample cross-validation procedure (Masyn, 2013) for the sample of Level 1 units (occasions). The sample size at Level 2 (N = 179 individuals), however, was not large enough to extend this cross-validation procedure to the between-person level. Future ESM studies with very large samples at both levels would allow for more stringent tests of robustness of the multilevel latent profile/class solution. The latent profiles of momentary ER and the latent classes of individuals (differing in their use of ER profiles over time) identified in the present study may be specific to the community sample collected in this study. Researchers are encouraged to apply the ML-LPA approach to ESM data of momentary ER strategy use to examine whether the profiles/classes replicate in other samples. Based on recent theoretical considerations on the use of multiple ER strategies in a single episode (emotion polyregulation; Ford et al., 2019), we would expect differences between ESM studies in context (e.g., sampling individuals during times of stress vs. during "calm" periods of their life) to have an effect on the number of different ER profiles and the specific configuration of ER strategies that are identified at the occasion level. Likewise, we would expect differences between studies in the targeted population (e.g., non-clinical vs. clinical samples) to have an effect on the type and distribution of latent classes at the person level.

Finally, our analyses that revealed mean differences in well-being between different ER repertoire classes of individuals are correlational. Hence, the data do not speak to the directionality of the link between ER repertoire and well-being. It is possible that individuals who use a more diverse profile of active ER strategies are better able to flexibly adapt their ER to the needs of the situation and are thus more successful at maintaining well-being in the face of stressors. But it is also possible that a higher level of well-being makes it easier for individuals to use a variety of active ER strategies and refrain from using suppression-focused ER strategies. Future studies might benefit from designs with multiple ESM phases to examine how well-being and ER repertoire predict each other over time.

Conclusion

By applying ML-LPA to ESM data, the current study extends previous research on ER repertoires by investigating how individual differences in profiles of momentary use of ER strategies across situations in daily life are related to indicators of well-being. Our findings advance knowledge about the adaptiveness of different ER repertoires by examining not only how different ER repertoires relate to deficits in well-being (i.e., measures of distress) but also how ER repertoires are associated with indicators of flourishing. Taken together, the current findings suggest that the specific content of an individuals' ER "toolbox" (and not simply its size) is important for the relation between ER repertoire and well-being.

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Table 1

Descriptive Statistics for the Momentary ER Strategies

				Range		
Strategy	M	SD_{within}	SD_{between}	Actual	Possible	ICC
Situation selection	59.47	22.98	19.80	0-100	0-100	.43
Situation modification	45.55	24.62	20.84	0-100	0-100	.42
Distraction	51.53	25.22	21.72	0-100	0-100	.43
Rumination	36.72	23.25	21.76	0-100	0-100	.47
Reappraisal	40.34	19.30	21.77	0-100	0-100	.56
Acceptance	60.70	20.10	22.66	0-100	0-100	.56
Suppression	38.54	24.61	22.66	0-100	0-100	.46
Social sharing	35.37	27.27	19.71	0-100	0-100	.34
Ignoring	31.71	23.20	18.99	0-100	0-100	.40

Note. M = grand mean (i.e., mean across occasions and individuals). SD_{within} = within-person standard deviation. SD_{between} = between-person standard deviation. ICC = intraclass correlation coefficient. Descriptive statistics were computed on the basis of multilevel null models for each strategy.

Table 2

Descriptive Statistics and Correlations among the Well-Being Measures

			Range		Correlations				
Well-being measure	*M*	*SD*	Actual	Possible	1	2	3	4	5
1. Life satisfaction	23.93	6.48	5.50-34.50	5-35					
2. Depression	3.67	3.52	0-20.50	0-21	-.55				
3. Anxiety	3.41	2.83	0-12	0-21	-.38	.60			
4. Stress	5.71	3.54	0-18	0-21	-.32	.59	.69		
5. Pleasant affect	62.87	13.33	26.46-98.36	0-100	.36	-.33	-.28	-.30	
6. Unpleasant affect	22.12	13.37	1.14-82.41	0-100	-.31	.39	.47	.44	-.46

Note. For all correlations, $N = 179$ and $p < .001$.

Table 3

Model Fit Statistics for LPA Models with Different Numbers of Level 1 Profiles (and One Level 2 Class)

Number of profiles	LL	BIC	Size of drop in BIC	AIC3	Size of drop in AIC3	Number of parameters	Entropy R^2 (L1)	Classification error (L1)	Smallest AvePP (L1)	Size of smallest P
1	-1276707.70	2553508.78		2553469.41		18	1.0000	.0000		
2	-1256984.04	2514113.32	39395.46	2514052.07	39417.34	28	.7936	.0582	1.0000	.3922
3	-1249323.89	2498844.90	15268.42	2498761.78	15290.29	38	.8207	.0664	.9301	.0943
4	-1242724.52	2485698.03	13146.87	2485593.04	13168.74	48	.8446	.0743	.9069	.0932
5	-1238794.50	2477889.87	7808.16	2477763.00	7830.04	58	.8207	.1082	.8384	.1060
6	-1233896.31	2468145.35	9744.51	2467996.61	9766.38	68	.8823	.0797	.8905	.0969
7	-1230468.73	2461342.07	6803.29	2461171.45	6825.16	78	.8822	.0871	.8276	.0635
8	-1227836.26	2456129.00	5213.07	2455936.51	5234.94	88	.8967	.0925	.8765	.0756
9	**-1223840.11**	**2448188.59**	**7940.41**	**2447974.23**	**7962.28**	**98**	**.9134**	**.0721**	**.8958**	**.0574**
10	-1221121.85	2442803.93	5384.66	2442567.69	5406.53	108	.9077	.0819	.8346	.0563
11	-1219561.08	2439852.27	2951.66	2439476.16	3091.54	118	.9154	.0767	.8471	.0190

Note. LL = log-likelihood. L1 = level 1. AvePP = average posterior class probability. P = emotion regulation profile on the occasion level. Bold indicates the selected model.

Table 4

Model Fit Statistics for LPA Models with Different Numbers of Level 2 Classes (and Nine Level 1 Profiles)

Number of classes	LL	BIC	Size of drop in BIC	AIC3	Size of drop in AIC3	Number of para-meters	Entrop y R^2 (L1)	Classifica-tion Error (L1)	Smallest AvePP (L1)	Entropy R^2 (L2)	Classifica-tion Error (L2)	Size of smalle st C
1	-1223840.11	2448188.59		2447974.23		98	.9134	.0721	.8958			
2	-1217526.89	2435608.82	12579.77	2435374.77	12599.45	107	.9166	.0687	.9057	.9988	.0002	0.4694
3	-1214499.76	2429601.25	6007.57	2429347.52	6027.26	116	.9208	.0655	9184	.9985	.0003	0.1685
4	-1211191.97	2423032.36	6568.90	2422758.93	6588.58	125	.9176	.0632	.9203	.9995	.0001	0.1682
5	**-1209336.21**	**2419367.52**	**3664.83**	**2419074.41**	**3684.52**	**134**	**.9252**	**.0618**	**.9228**	**.9990**	**.0003**	**0.1289**
6	-1208349.03	2417439.86	1927.66	2417127.06	1947.35	143	.9252	.0618	.9256	.9996	.0001	0.0787
7	-1207550.46	2415889.40	1550.46	2415556.92	1570.14	152	.9075	.0785	.8935	.9987	.0005	0.0730

Note. LL = log-likelihood. P = emotion regulation profile on the occasion level. C = classes of individuals. L2 = level 2. Bold indicates the selected model.

Table 5

Model Fit Statistics for LPA Models with Different Numbers of Level 1 Profiles (and Five Level 2 Classes)

Number of profiles	LL	BIC	Size of drop in BIC	AIC3	Size of drop in AIC3	Number of parameters	Entropy R^2 (L1)	Classification error (L1)	Smallest AvePP (L1)	Size of smallest P
1	-1276707.70	2553529.53		2553481.41		22	1.0000	.0000	1.0000	
2	-1248846.47	2497879.68	55649.85	2497800.94	55680.47	36	.8889	.0443	.9454	.3944
3	-1237697.40	2475654.17	22225.52	2475544.80	22256.14	50	.8673	.0505	.9333	.1171
4	-1228007.42	2456346.84	19307.33	2456206.85	19337.95	64	.8874	.0539	.9193	.0945
5	-1222487.20	2445379.01	10967.83	2445208.39	10998.45	78	.8742	.0730	.8887	.1080
6	-1219008.16	2438493.55	6885.46	2438292.31	6916.08	92	.8875	.0757	.9021	.0925
7	-1215398.41	2431346.68	7146.88	2431114.81	7177.50	106	.8821	.0870	.8502	.0841
8	-1212188.44	2424999.36	6347.31	2424736.88	6377.94	120	.8908	.0852	.8478	.0438
9	**-1209336.21**	**2419367.52**	**5631.84**	**2419074.41**	**5662.46**	**134**	**.9252**	**.0618**	**.9228**	**.0569**
10	-1206443.43	2413654.59	5712.93	2413330.86	5743.55	148	.9155	.0749	.8348	.0568
11	-1204436.08	2409712.52	3942.07	2409358.17	3972.69	162	.9129	.0806	.8256	.0503

Note. LL = log-likelihood. P = emotion regulation profile on the occasion level. C = classes of individuals. L1 = level 1. AvePP = average posterior class probability. Bold indicates the selected model.

Table 6

Means and Standard Deviations (in Parentheses) of Well-Being Measures for Different Classes of Individuals

Classes of Individuals	Life satisfaction	Depression	Anxiety	Stress	Pleasant affect	Unpleasant affect
C1: “diversity of profiles (suppression focus)”	21.63 (6.66)[a]	4.89 (4.11)[a]	4.45 (2.90)[a]	6.67 (3.87)[a]	59.81 (13.54)[a]	23.81 (13.47)[a]
C2: “diversity of profiles (active regulation focus)”	25.40 (6.94)[b]	2.83 (2.83)[b]	2.23 (2.10)[b]	4.69 (3.04)[b]	68.11 (11.66)[b]	15.01 (8.02)[b]
C3: “predominantly multi-ER (moderate level) profile”	24.52 (5.43)[ab]	3.31 (2.93)[ab]	3.94 (2.98)[ac]	5.58 (3.48)[ab]	58.15 (10.45)[a]	30.72 (11.96)[c]
C4: “predominantly no ER profile”	24.80 (6.66)[ab]	3.74 (3.82)[ab]	2.09 (1.90)[bc]	6.41 (3.33)[ab]	57.27 (10.39)[a]	15.68 (8.35)[ab]
C5: “predominantly multi-ER (high level) profile”	24.43 (5.65)[ab]	2.90 (3.53)[ab]	3.73 (3.49)[abc]	4.70 (3.56)[ab]	80.16 (9.69)[c]	22.21 (19.70)[abc]
Effect size η^2	.05	.06	.12	.05	.25	.21
Wald test χ^2 (df = 4)	9.37$^+$	9.28$^+$	29.96**	10.65*	78.68***	64.43***

Note. Superscripts showing different letters within a given column indicate significant mean differences between classes (adjusted $p <$ .05 on the basis of Tukey’s Honest Significant Difference). Wald test results are based on adjusted three-step approach.

$^+$ $p < .06$. * $p < .05$. ** $p < .01$. *** $p < .001$.

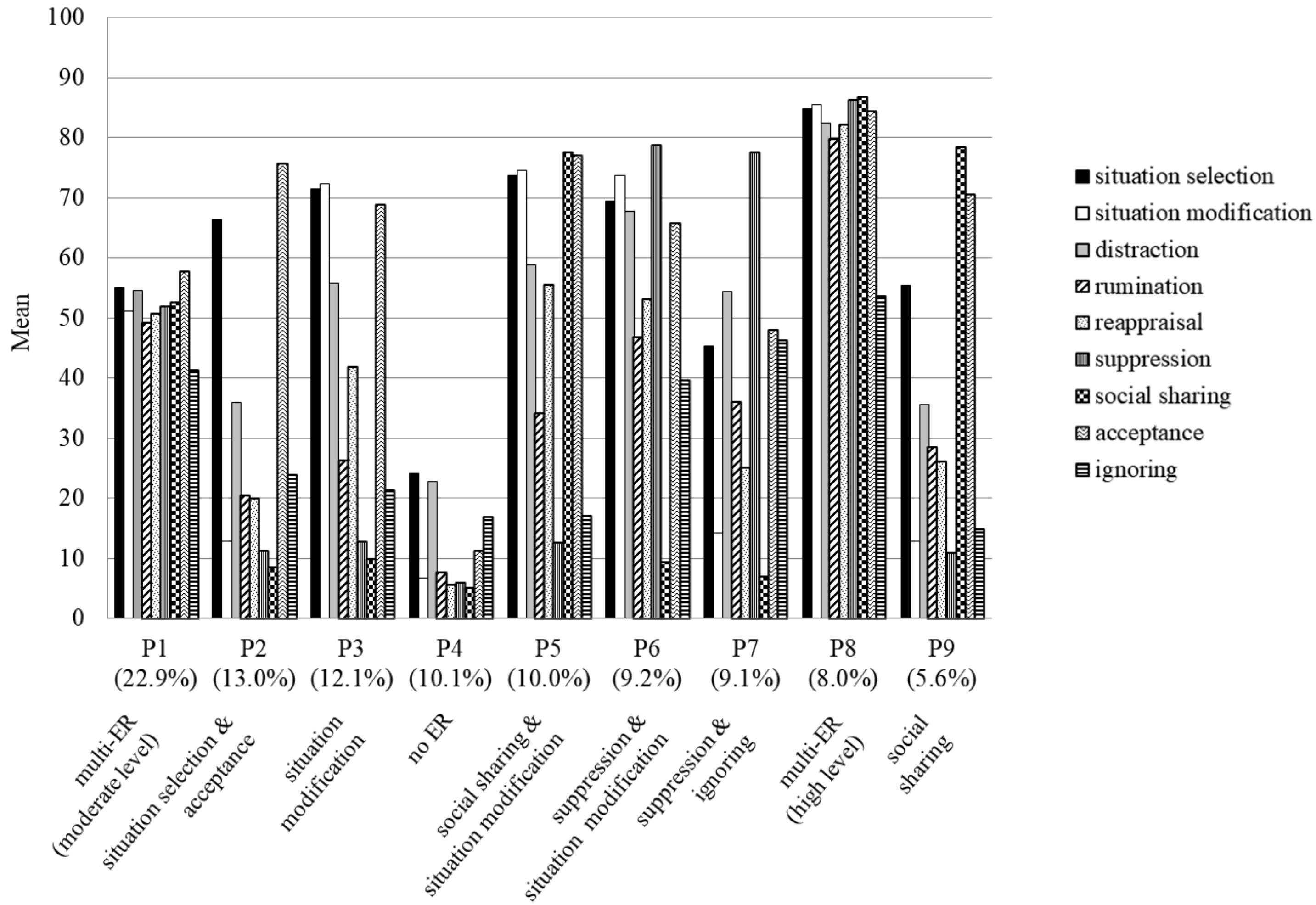

Figure 1a. Latent profiles of momentary ER (from the model with nine profiles on the occasion level). Bars represent mean scores on each strategy for the respective profile. Numbers in parentheses represent profile sizes (i.e., percentage of occasions that are assigned to a profile). P = emotion regulation profile on the occasion level.

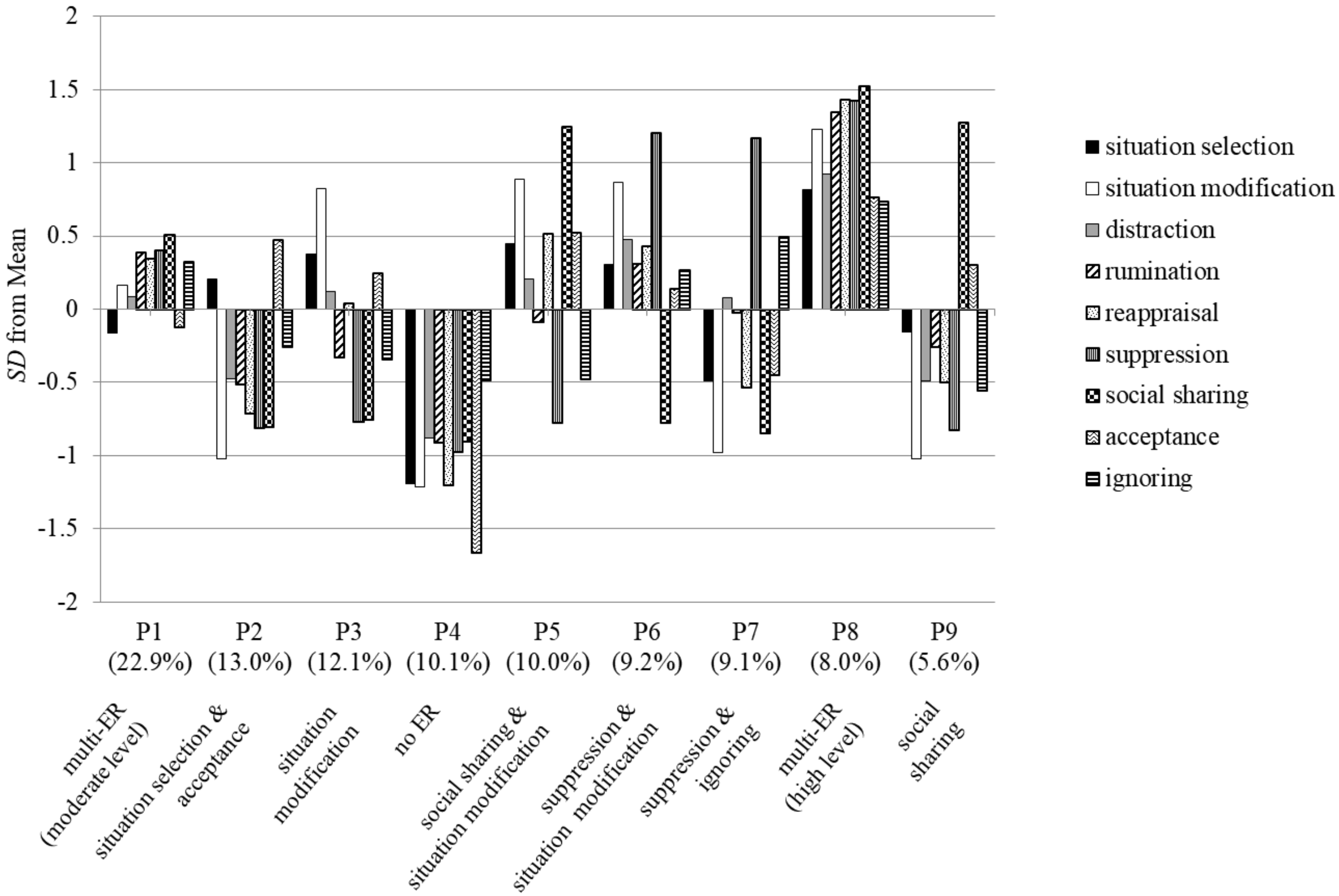

Figure 1b. Latent profiles of momentary ER (from the model with nine profiles on the occasion level). Bars represent standard deviations from the overall sample mean. Numbers in parentheses represent profile sizes (i.e., percentage of occasions that are assigned to a profile). P = emotion regulation profile on the occasion level.

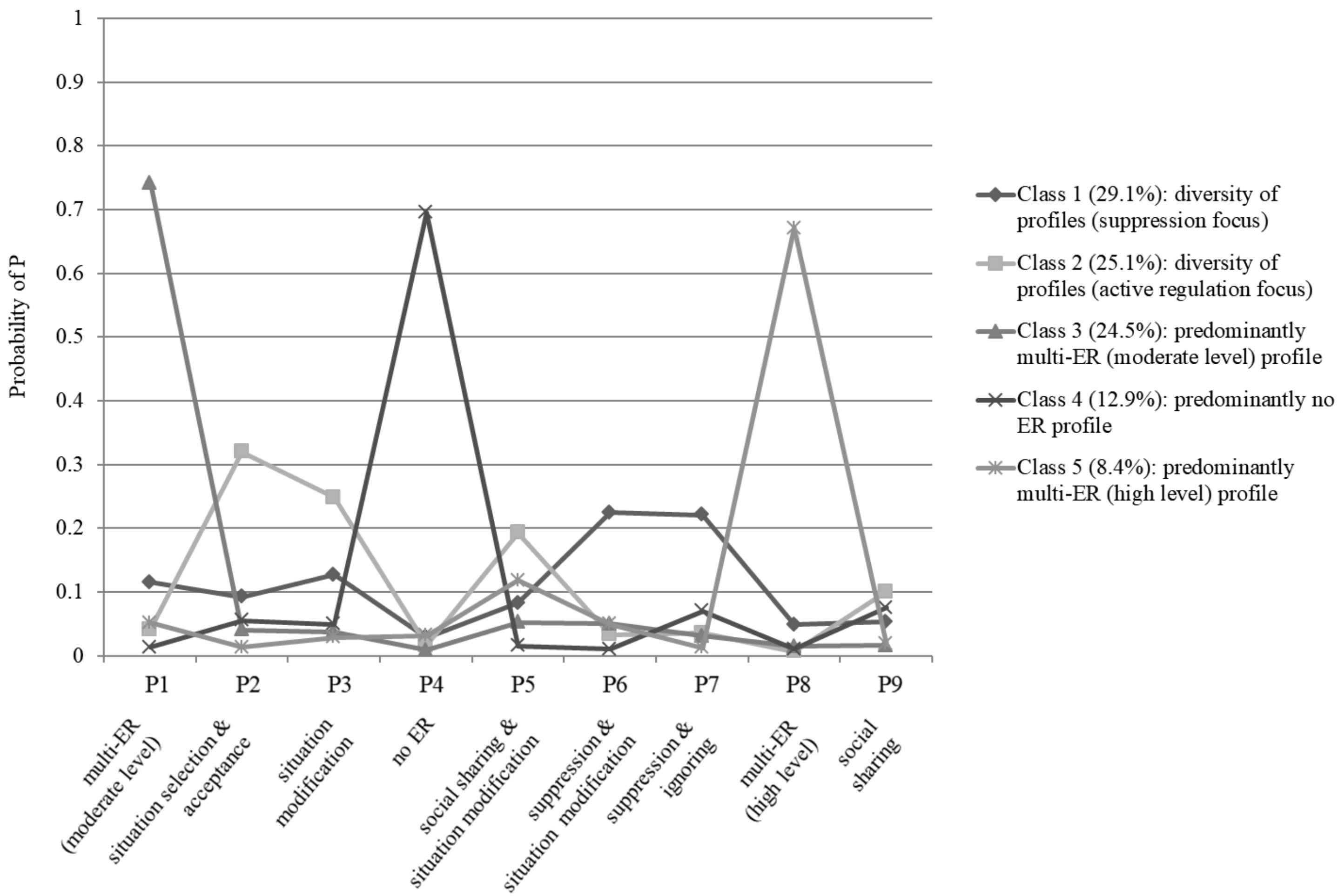

Figure 2. Latent classes of individuals differing in the distribution of occasion-level ER profiles over time (final ML-LPA model with nine ER profiles on Level 1 and five classes of individuals on Level 2). Numbers in parentheses represent class sizes (i.e., percentage of individuals assigned to a class). P = emotion regulation profile on the occasion level.