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RESEARCH

Handling the Ups and Downs of Adolescence: The Role of Emotion Regulation Repertoires

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Abstract
Adolescence is a period of biopsychosocial change, where some youth thrive while others develop stress-related difficulties, making it crucial to understand the processes that may contribute to poor mental health. This study examined adolescents' emotion regulation (ER) repertoires and their associations with indicators of mental health, using data pooled across three waves of ecological momentary assessment (EMA), each spaced six months apart. The final sample included 292 adolescents (M_{age} = 12.55 years, SD_{age} = 0.46; 41.48% female) who reported their use of seven ER strategies and affect five times daily over two weeks in each wave. In wave 3, participants completed questionnaires assessing depressive and anxiety symptoms, emotional eating, and loneliness. Multilevel latent profile analysis identified six occasion-level ER profiles that differed in size (from no strategy use to moderate use of all strategies) and composition (adaptive versus maladaptive strategies). At the person-level, three distinct classes emerged: a multi-ER class (moderate use with fewer adaptive strategies), a no-ER class (minimal strategy usage), and a high adaptive class (frequent use of adaptive strategies). Mental health outcomes differed across groups: adolescents in the no-ER class reported the most favorable outcomes (lower depressive and anxiety symptoms, higher daily positive affect), whereas those in the multi-ER class showed the poorest outcomes. The high adaptive class displayed a mixed pattern, with higher levels of daily positive affect similar to the no-ER group but higher levels of daily negative affect resembling the multi-ER group. These findings challenge the assumption that a larger ER repertoire is inherently beneficial, emphasizing the importance of repertoire composition and contextual fit. Interventions could focus on teaching adolescents context-sensitive combinations of strategies, and future studies should evaluate their effectiveness in improving mental health.

Keywords Adolescence · Emotion regulation repertoires · Mental health · Multilevel latent profile analysis

Adolescence is a developmental period marked by profound biopsychosocial changes that strongly impact how emotions are experienced and regulated (Dahl et al., 2018; Riediger, 2024). Adolescents often report heightened emotional intensity and reactivity compared to both children and adults (Dahl et al., 2018; Somerville et al., 2010). This shift is thought to reflect neurodevelopmental changes in which subcortical regions involved in emotion processing (e.g., the amygdala) mature earlier than prefrontal regions responsible for regulation and control (Luciana, 2013). While many adolescents navigate these changes successfully, others develop symptoms of stress-related disorders such as anxiety and depression (Shorey et al., 2022). Understanding why some adolescents thrive while others struggle is a crucial question in mental health research. One potential explanation lies in individual differences in the ability to regulate emotions successfully (Aldao et al., 2010).

Emotion regulation (ER) can be defined as a set of strategies that are used to influence which emotions one has, when one has them, and how these emotions are experienced or expressed (Gross, 2015). To regulate emotions and to cope

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with stressors, individuals can employ a range of cognitive (e.g., distraction, cognitive reappraisal) and behavioral (e.g., social support) strategies. Although a growing body of research highlights that regulation of both negative and positive affect (e.g., excitement, joy; van Roekel et al., 2024) plays a critical role in individual well-being, building on the dominant ER literature in this study we specifically focused on emotion regulation in response to negative emotional experiences (i.e., sadness, anger, fear). ER difficulties are consistently linked to a broad range of emotional and behavioral outcomes during adolescence. To capture this complexity, we use *mental health* as an umbrella term encompassing internalizing symptoms (depressive, anxiety symptoms), and psychosocial distress symptoms and behaviors (emotional eating, loneliness and daily-life affect). These indicators represent key aspects of adolescents' psychosocial functioning that are closely tied to ER capacities (Aldao et al., 2010; Schäfer et al., 2017). For instance, less adaptive labeled ER strategies have been associated with higher depressive and anxiety symptoms, greater loneliness, and greater reliance on maladaptive coping behaviors in both adolescents and adults (Aldao et al., 2010; Schäfer et al., 2017). Examining these outcomes together allows for a more comprehensive understanding of how ER relates to adolescents' overall mental health.

Much research to date has focused on determining the benefits and costs of individual strategies (Kraft et al., 2023; Schäfer et al., 2017). While this research has advanced our understanding of individual ER strategies, growing evidence indicates that individuals typically use different strategies across situations in a flexible, context-dependent manner, drawing on a broader *strategy repertoire* (Bonanno & Burton, 2013). Strategy repertoire includes two relevant dimensions: size, referring to the total number of unique strategies (e.g., a repertoire consisting of five versus ten strategies), and composition, referring to the specific ER strategies included in the repertoire (e.g., those typically deemed adaptive, maladaptive, or a mix of both). Having access to a wider range of strategies—that is, having a larger repertoire— is likely to provide people with the necessary tools to engage in more complex forms of ER, such as using multiple strategies within a single emotional episode (i.e., polyregulation; Ford et al., 2019). These perspectives challenge the static classification of strategies as universally adaptive or maladaptive, highlighting that the effectiveness of a strategy depends on situational fit. For instance, distraction may be helpful in highly stressful situations, while reappraisal may be more effective in low intensity contexts (Ford & Troy, 2019).

Building on these theoretical perspectives, it is important to examine how adolescents combine and switch between strategies in daily life, rather than focusing solely on the use of individual strategies. Previous findings indicate that having a larger strategy repertoire is associated with more positive outcomes and better mental health, such as fewer depressive symptoms (Eldesouky & English, 2018; Lougheed & Hollenstein, 2012; Southward et al., 2018). However, emerging research using adult samples suggests that repertoire composition may matter more than size alone (Baldwin et al., 2025; Grommisch et al., 2020; Guassi Moreira et al., 2024). For example, one study found that consistently using a diverse range of putatively *adaptive* strategies (e.g., reappraisal) but not putatively *maladaptive* strategies (e.g., suppression) was associated with fewer depressive and anxiety symptoms than using all strategies frequently (i.e., a mix of both putatively adaptive and maladaptive strategies) or using no to low ER (Guassi Moreira et al., 2024). In other words, the benefits of a broad strategy repertoire likely depend on using more effective strategies (i.e., strategies that match the situational demands) and not simply more strategies.

Although there appears to be a consensus on the benefits of studying ER repertoires rather than single strategies in isolation (Kalokerinos & Koval, 2024), how strategy repertoire is measured varies greatly across studies. One of the most common approaches is to simply calculate the total number of unique strategies a person habitually uses (e.g., Werner et al., 2025) either in response to emotion-evoking stimuli or situations in experimental paradigms (e.g., Eldesouky & English, 2018; Quiñones-Camacho & Davis, 2018) or in response to hypothetical scenarios (e.g., Southward et al., 2018). However, this approach does not fully reflect the composition of the repertoire. A second approach consists of assessing individuals' trait levels of ER and extracting specific ER profiles (i.e., different combinations of strategies) using person-centered analyses (e.g., De France & Hollenstein, 2017; Dixon-Gordon et al., 2015; Lougheed & Hollenstein, 2012). Although this approach allows the assessment of both repertoire size and composition, relying on trait-level ER (e.g., habitual strategy use) may be biased by people's beliefs regarding the strategies that they generally use. To overcome these limitations, a third, less common approach uses ecological momentary assessment (EMA) to extract ER profiles based on how people regulate emotions in daily life. For instance, Grommisch et al. (2020) identified nine occasion-level profiles and five person-level classes. It was found that individuals who used diverse and active ER strategies reported less anxiety symptoms, stress and daily negative affect, while those relying mainly on suppression experienced more symptoms. This EMA approach offers the advantage of identifying ER profiles based on repertoire size and composition in an ecologically valid way while also assessing how people vary in their use of these profiles over time (see Fig. 1 for an illustration).

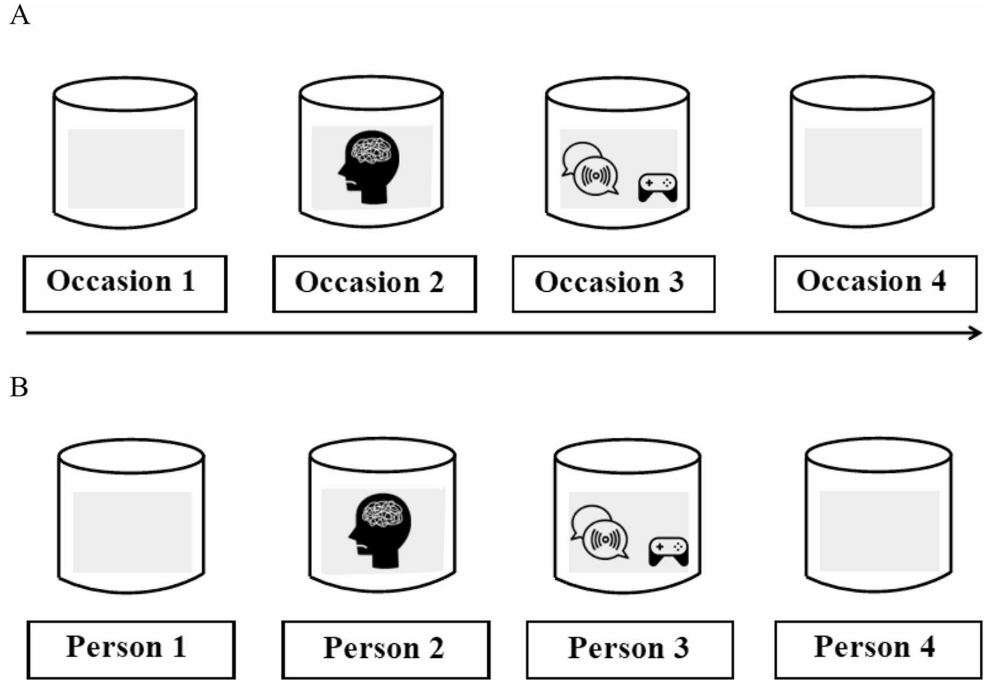

Fig. 1 Visual Explanation of Occasion-Level Profiles and Person-Level Classes A. *Note*. Figure 1A presents a visual example of occasion-level profiles, participants can select a range of different strategies on each occasion (e.g., on occasion 1 they chose to use no emotion regulation strategies - empty glass; on occasion 2 they chose rumination, and on occasion 3 they chose a mix which included distraction and social sharing). Figure 1B presents a visual example of person-level classes. Although participant can select multiple mixes/profiles of strategies during different occasions, they may have a personal preference for a specific profile (e.g., person 1 and 4 have a preference for the no strategies profile, while person 2 has a preference for the rumination profile)

The current study aimed to extend prior research on adolescent ER by examining ER as a context-dependent process in daily life using a person-centered approach across three waves of EMA data, thereby capturing both the size and composition of adolescents' ER repertoires and their associations to indicators of mental health. Specifically, we addressed two research questions (RQs): (1) Can different latent profiles and classes of ER be identified? (RQ 1), and (2) Are strategy repertoires associated with indicators of mental health? (RQ 2). To address these questions, we first extracted profiles at the occasion-level (i.e., at each EMA survey), in order to determine adolescents' strategy repertoire at each occasion, and subsequently used these profiles to group adolescents into person-level classes based on their profile preferences across all occasions (RQ 1). Next, we examined whether the identified ER repertoires were related to various indicators of mental health, including depressive symptoms, anxiety symptoms, loneliness, emotional eating, and daily-life affect (RQ 2). Based on prior theoretical (Bonanno & Burton, 2013) and empirical work (e.g., Grommisch et al., 2020; Guassi Moreira et al., 2024; Southward et al., 2018), we hypothesized that adolescents would differ in their use of ER strategies across different measurement occasions (i.e., different EMA surveys), both in the number of strategies used (i.e., size; no vs. high usage) and composition of strategies (e.g., suppression-focused vs. reappraisal-focused). Finally, we hypothesized that adolescents with a preference for a diversity of occasion-level profiles would experience fewer internalizing symptoms and less social-emotional distress, as such preference may reflect their ability to select and use the most appropriate set of strategies depending on the specific situational demands (Guassi Moreira et al., 2024). This approach extends prior research by capturing ER as a context-dependent process in daily life, thereby addressing a key gap in understanding how adolescents regulate emotions across real-world contexts.

Method

Participants

For the current study, EMA data were used from a large longitudinal project (i.e., Outside-In; Debra et al., 2024; Debra et al., 2025) which aimed to examine different mechanisms underlying the aversive effects of victimization in adolescents. This project included a measurement-burst design, with EMA data collected at three different waves within the same cohort of adolescents. Data collected across all three waves were used to address the research questions.

A total of 266 adolescents enrolled in the first year of nine secondary schools in Belgium (Flanders region) completed the first EMA wave in the fall of 2021 (M_{age} = 12.49 years, SD_{age} = 0.43; 58.89% males). Approximately 6 months later, in the spring of 2022, 265 adolescents participated in the second wave of EMA. Of these, 17 were excluded because they completed fewer than three EMA surveys or failed to meet the accuracy standards for the control items (see the Procedure section for more details). As a result, the final sample for wave 2 included 248 adolescents, 231 of whom also participated in the first wave of EMA (93.15% of the wave 1 sample). Finally, 244 adolescents participated in the third EMA wave during the fall of the second year of secondary school (approximately 1 year after the first EMA). In wave 3, eight adolescents were excluded because they either did not complete enough EMA surveys (<3) or failed to pass the accuracy score check (see *Procedure*), resulting in a final sample of 236 adolescents for wave 3. Of these adolescents, 227 participated in wave 1 (96.19%), 215 participated in wave 2 (91.10%), and in total 205 participated in both wave 1 and 2 (86.44%).

Because we used the same measures across the three different waves, we pooled the waves to enhance the power to determine the occasion-level profiles and person-level classes under the assumption that profiles and classes remained consistent across the three waves (for more information see *Model selection* in the Methods and Results sections, and Tables S1-S3 in Supplementary Information). All participants who participated in one, two, or all three EMA waves were included in the final analytic sample. The final analytic sample consisted of 292 participants (M_{age} = 12.53 years, SD_{age} = 0.47; 41.10% female), of which 205 adolescents participated in all three waves, 48 adolescents participated in two of the three waves, and 39 adolescents completed one wave only. For an overview of percentages of participants per wave, please see Table S4 in Supplementary Information. Overall, the sample consisted of adolescents predominantly of Belgian nationality, with most living in two-parent households. Across all three waves, a large proportion of parents had attained higher education qualifications. Descriptive statistics for each wave are presented in Table S5 in Supplementary Information.

Procedure

All procedures were approved by the medical ethical committee of UZ Ghent and Ghent University. All adolescents provided written assent and their parents signed an informed consent form prior to the start of the study. There were no further inclusion or exclusion criteria. At each wave, before the EMA, participants completed a series of questionnaires on tablets to assess several psychological variables, including depressive and anxiety symptoms, loneliness, and emotional eating.

Prior to the start of each EMA wave, all participants received an information session concerning the full study procedure, as well as specific information related to the EMA questions, expectations, and timing schedules. Afterward, all participants installed the m-Path EMA app (www.m-path.io) on their smartphone. A fixed time-based sampling schedule was used: a total of five surveys were distributed per day for a total of 14 consecutive days (10 weekdays and two weekends; 70 surveys in total). Importantly, surveys were sent before school, during school hours, and after school. The timing schedule was consistent across participants on weekends; however, during school days it could vary slightly to accommodate adolescents' school schedules and avoid interfering with educational activities. At each signal, participants received a notification on their smartphones from m-Path to complete a survey, and they were required to fill in the questions within 50 min (for the first three surveys), within 90 min (the fourth survey), and within 120 min from the prompt (final survey; see Debra et al., 2025).

Consistent with EMA guidelines (van Roekel et al., 2019), two approaches were followed to maximize participants' compliance rate. First, incentives were determined based on participants' compliance rates. At each wave, a gift voucher worth €20 was given to adolescents who completed at least 70% of surveys, while a voucher worth €10 was given to participants who completed between 50% and 69% of surveys. Second, participants' compliance rates were actively monitored throughout the study, and text messages were sent after two days of low compliance.

EMA surveys were completed in participants' daily-life contexts (both at home and during school hours). During Wave 1, research staff were present at participating schools to provide technical support and collect saliva samples (see Lorenz et al., 2025); if participants forgot their smartphone or experienced app difficulties while at school, they were offered a paper version of the survey to complete (135 times). A total of 18,364 EMA prompts (18,229 online and 135 on paper) were triggered across the 266 participants, which was slightly below the expected 18,620 due to technical issues. This resulted in 26 participants receiving fewer than the intended 70 surveys (range: 7–69 $Mdn = 67.5$). Additionally, 32 EMA prompts were excluded as they were not completed within the designated time limits (50, 90, or 120 min). Out of the remaining 18,332 prompts, 12,779 were fully completed, resulting in an overall compliance rate of approximately 69.7%, based on the number of surveys received by each participant. Notably, the majority of participants (84.73%) completed at least half of the surveys they received.

Starting from wave 2, a control item was included in each survey, to minimize and identify instances of careless responding (e.g., random answers). Participants were shown a row of seven horizontally aligned dots and were instructed to select the dot on either the far left or the far right (e.g., "Tap the dot most right; the number 7 will appear afterwards" or "Tap the dot most left; the number 1 will appear afterwards"). When a dot was tapped, a number indicating its position appeared to reduce potential errors caused by confusion between left and right. The control items were placed randomly within each survey, with their position varying between participants; the specific instruction (left or right) also varied. To ensure these items were not easily distinguishable, they were visually similar to the other survey items. Accuracy was calculated as the proportion of correct responses relative to the total number of completed surveys. Participants with an accuracy score of 80% or lower ($n = 14$) were excluded in advance. Among the 248 participants included in the final sample, 17,360 surveys were scheduled, and 12,089 surveys were completed. Due to technical issues, 25 participants received fewer than the expected 70 surveys (range: 26–69, $Mdn = 69$). Based on the number of surveys participants received, the average compliance rate was approximately 70%, with 199 participants (80.5%) completing at least half of the surveys.

As in wave 2, a control item was included in each wave 3 survey. Participants were presented with a Dutch word containing two to seven letters and were asked to count and report the number of letters. Five participants were excluded from the main analyses beforehand, as their accuracy scores were below 80% (see also Debra et al., 2024). Among the 236 participants included in the final sample, a total of 10,793 surveys were completed within the allowed time limit. Due to technical difficulties, eight participants received fewer than the 70 planned surveys (range = 35–69, *M*dn = 66.5). Furthermore, 27 surveys were excluded because they were completed too late, and an additional eight surveys were removed due to technical issues (i.e., duplicate surveys sent). Based on the number of surveys participants received, the average compliance rate was approximately 64.45%, which is consistent with prior EMA in adolescents (van Roekel et al., 2019).

Ecological Momentary Assessment Measures

Emotion Regulation Strategies (wave 1–3)

A two-step approach was used to assess participants' usage of ER strategies in daily life (De France & Hollenstein, 2019). In wave 1, participants were first asked to select the most unpleasant emotion experienced since the previous survey (or since awakening) from a list of three options (sad, angry, or scared) and then rate its intensity. In waves 2 and 3, this emotion-selection step was omitted to simplify the procedure: participants were instead asked to think about their most negative emotion experienced since the previous survey (or since awakening) without specifying which emotion it was. Subsequently, they had to rate the emotion intensity on a scale from 1 ("not intense") to 7 ("very intense").

In a second step, in all waves, participants were asked to indicate to what extent they had used seven different ER strategies to regulate the experienced negative emotions. More specifically, single items were used to assess participants' usage of distraction ("I did other things to distract myself"), cognitive reappraisal ("I changed the way I thought about the situation"), engagement ("I tried to express my emotions"), suppression ("I tried to hide my feelings"), and rumination ("I could not stop thinking about it"). All items were selected from the Regulation of Emotions Systems Survey- Ecological Momentary Assessment (RESS-EMA; Medland et al., 2020) questionnaire. Next, one item was used to assess social sharing ("I have talked about the situation with others") (Brans et al., 2013). Lastly, two items were used to assess participants' usage of self-compassion, the items were taken from the Dutch version of the Emotion Regulation Skills Questionnaire (ERSQ; Berking & Znoj, 2008; "I supported myself.", "I tried to cheer myself up."). However, to be consistent with the other ER strategies, we selected the "I supported myself" item as self-compassion assessment, as it aligns best with the definition of self-compassion (Berking & Whitley, 2014). Adolescents had to indicate the extent to which they had used the different strategies since the previous assessment, by rating a 7-point rating scale ranging from 1 ("totally not") to 7 ("totally").

Daily-life Affect (wave 3)

Participants' negative and positive affect were assessed using nine items that tapped into both low and high arousal emotions. These items were adapted from the Positive and Negative Affect Scale for Children (PANAS-C; Laurent et al., 1999; Watson et al., 1988) and selected from prior research (e.g., Brans et al., 2013; Lennarz et al., 2019; Orth et al., 2022). Six items were used to capture a variety of negative emotions (e.g., sad, angry, anxious, uncertain, annoyed, and stressed), while three items measured positive affect (e.g., happy, energetic, and relaxed). The selection of these items aimed to balance high- and low-arousal positive and negative emotions, in line with research emphasizing the significance of considering both valence and arousal dimensions of affect (Weidman et al., 2017).

In each assessment, participants rated the intensity of each emotion on a scale from 1 ("totally not") to 7 ("totally") based on how they felt in that moment. Momentary scores for negative and positive affect were calculated by averaging the responses to the negative affect items and the positive affect items, respectively. These momentary scores were then combined across all measurement sessions to compute an average score for each participant throughout the 14-day EMA phase (wave 3). This approach follows previous EMA research using similar composite scores (e.g., Grommisch et al., 2020). McDonald's omega coefficients (ω) were calculated via multilevel confirmatory factor analyses (Geldhof et al., 2014) as an indicator of between- and within-person reliability. These reliability indicators were deemed satisfactory for positive ($\omega_{between}=0.88$; $\omega_{within}=0.59$) as well as negative affect ($\omega_{between}=0.94$; $\omega_{within}=0.70$).

Trait-Level Measures (wave 3)

Depressive Symptoms

A Dutch version of the *Short Mood and Feelings Questionnaire* (SMFQ; Angold et al., 1995) was used to assess depressive symptoms. The SMFQ consists of 13 items and was developed as a screening tool for detecting meaningful symptoms of depression in children and adolescents. All items (e.g., "I did everything wrong") were rated on a 3-point rating scale ranging from 1("not true") to 3 ("true"). Prior research in children and adolescents has demonstrated that the SMFQ has good internal reliability and a moderate diagnostic accuracy with a sensitivity of 0.66 and a specificity of 0.61 (Angold et al., 1995; Rhew et al., 2010). In this sample, ω was 0.92.

Anxiety Symptoms

Anxiety was measured using two subscales from the Dutch translation of the *Screen for Child Anxiety Related Emotional Disorders* (SCARED; Birmaher et al., 1997). Participants responded to nine statements assessing generalized anxiety disorder symptoms (e.g., "I worry about other people liking me," "I am nervous") and four statements assessing social phobia symptoms (e.g., "I don't like to be with people I don't know well," "I feel nervous with people I don't know well"). They rated how often they experienced these feelings using a rating scale from 1 ("almost never") to 3 ("often"). The 4-item social phobia subscale was used consistent with the original SCARED scoring (Birmaher et al., 1997) and prior adolescent studies (e.g., Hale et al., 2005). An overall anxiety score was calculated by averaging all items, with higher scores reflecting greater anxiety symptoms. Prior work has demonstrated that the SCARED has good psychometric properties (Hale et al., 2005). In our sample, ω was 0.89.

Loneliness

The *Roberts UCLA Loneliness Scale* (RULS-8; Roberts et al., 1993), was used to assess loneliness. Eight items (e.g., "I don't feel close to anyone yet") were rated on a 5-point rating scale ranging from 1 ("Completely untrue") to 5 ("Completely true"). This measure has been shown to be a reliable and valid measure to assess loneliness in adolescence (Goossens et al., 2014). In our sample, ω was 0.81.

Emotional Eating

A Dutch version of the *Three-Factor Eating Questionnaire – R21* (TFEQ-R21; Stunkard & Messick, 1985) was used to measure emotional eating behavior. The scale consists of six items (e.g., "When I feel sad, I often eat too much") which were rated on a 4-point rating scale ranging from 1 ("Totally false") to 4 ("Totally true"). Prior work has demonstrated that the TFEQ is a reliable and robust instrument to study different types of eating behavior (Duarte et al., 2020). In our sample, ω was 0.92.

Data Analysis

Sample Determinations

There are currently no simple tools to calculate the required sample size for Latent Profile Analyses (LPA) (Ferguson et al., 2020). Typically, between 300 and 500 individuals are needed to conduct LPA with one measurement per individual (Ferguson et al., 2020). In the current study, EMA was used which yielded multiple measurements (Level-1) per wave nested within each individual (Level-2). Therefore, multilevel LPA (ML-LPA) was used, in which both the number of participants and the number of measurements are important for sample determination. For ML-LPA, the required sample size has been suggested to depend on the expected number of profiles and the distinctiveness between the profiles (e.g., diversity in means on ER strategies), with higher distinctiveness, and a larger number of indicators yielding higher power (Park & Yu, 2018). In a simulation study with ML-LPA, it was found that 50 measurements per individual, across different Level-2 sample sizes, yielded more than 96% of simulation replications in which the total number of Level-1 and Level-2 classes was correctly estimated. On the other hand, with a total sample of 100 individuals (across different Level-1 sample sizes), in 89% of occasions Level-1 classes could not be correctly estimated (Lukočienė et al., 2010). In the only prior study applying ML-LPA to examine a similar research question (Grommisch et al., 2020), 29,956 measurement occasions nested in 179 participants were completed, of which ER profiles and classes were extracted (Grommisch et al., 2020). Therefore, data across the three EMA waves were merged to allow a reliable determination of profiles with 35,661 measurement occasions nested within 292 adolescents.

Identification of Latent Profiles and Classes of Emotion Regulation (RQ 1)

Data preparation and analyses were conducted using R (version 4.3.3), RStudio (version 2023.03.0), and Latent

Gold (version 6.1) (Vermunt & Magidson, 2025). The current study hypotheses and data analytic approach were not preregistered due to the data driven nature of the analyses. However, data and code were made available on The Open Science Framework (OSF; https://osf.io/2a7yf/). Latent profiles of ER strategies were obtained using a series of ML-LPA to account for the nested structure of the data (measurements nested within waves, nested within persons) in Latent Gold. Latent profiles of ER strategies in daily life were computed at the occasion-level (Level-1). At Level-2, we computed latent classes of adolescents who differed in their use of these ER profiles. Even though Level-2 technically refers to the waves (individuals could switch classes between waves), we refer to these classes as person-level classes, since they indicate differences between persons within a specific wave as well as within a person across waves. Person-level classes reflect differences in the probability of endorsing different ER profiles (Grommisch et al., 2020). We accounted for the within-person dependency of observations across waves by modeling the individuals as a grouping variable at Level-3.

All analyses were conducted with maximum likelihood estimation. The different models were estimated by using 500 initial starting values to avoid local maxima. To identify an optimal model with adequate number of latent profiles and latent classes, we followed a three-step approach proposed by Lukočienė et al. (2010), as well as recommendations from Ferguson et al. (2020). In a first step, we evaluated a series of plausible LPA models at Level-1 to determine profiles of momentary ER at the occasion-level, while accounting for the within-person dependency of the measurement occasions. Specifically, we started with a model containing two profiles at Level-1 and one class at Level-2, and progressively estimated models with more profiles until the inclusion of further profiles did not result in a better fit compared to the previous model. Data from all three waves were merged to determine the Level-1 profiles, based on the assumption that profiles would remain consistent across waves. To verify this assumption, step 1 was also conducted separately for each wave (see Tables S1-S3 for fit indices in Supplementary Information). In a second step, we specified a series of ML-LPA to assign adolescents to their most likely ER profile(s) using the posterior probabilities from the previous Level-1 analysis. More specifically, we fixed the number of Level-1 profiles based on results from the first step but varied the number of Level-2 classes. Finally, in a third step, we fixed the number of Level-2 classes (based on results of the second step), to reevaluate the number of Level-1 profiles, while accounting for the three-level structure of the data by including the persons as a grouping variable at Level-3 (see Grommisch et al., 2020).

At each analytic phase, different criteria were used to determine the best model fit. Specifically, model comparison was based on model fit indices, profile stability, and whether profiles and classes were meaningful based on theoretical interpretability and previous findings (Grommisch et al., 2020). We compared the models' goodness of fit using Bayesian Information Criterion (BIC; Schwarz, 1978). Following the simulation studies by Lukočienė and colleagues (2010) the BIC based on the sample size at Level-2 (i.e., 750)[1] was preferred as goodness-of-fit criterion over the BIC based on the sample size at Level-1 (which refers to the number of measurement occasions; i.e., 35,611 completed EMA surveys). Similar to previous studies (e.g., Grommisch et al., 2020), information criteria values are expected to continue decreasing as the number of profiles and classes increases, even when Level-1 profiles and Level-2 classes may not represent meaningfully different subgroups (e.g., Masyn, 2013). Therefore, we examined whether the extent of the decrease in BIC flattened out at a given point (Nylund et al., 2007). Next, we inspected profile/class stability using two indicators of latent profile and class separation quality: entropy (R-squared) and the average posterior class probability. Entropy values of ≥ 0.70 are generally considered acceptable for distinguishing latent classes, while average posterior class probability values of ≥ 0.80 indicate good classification accuracy (Grommisch et al., 2020; Masyn, 2013).

Emotion Regulation Repertoires and Mental Health (RQ 2)

After determining the person-level classes, the most likely class membership was extracted for each participant. These were used to examine differences across classes in depressive symptoms, anxiety, emotional eating, loneliness, positive, and negative affect assessed at wave 3. Specifically, we performed a series of ANOVA tests to determine whether the person-level classes differed significantly in the aforementioned outcomes. If statistically significant differences across classes were identified, multiple comparisons between all classes were performed, with adjustments for multiple testing applied using Tukey's honestly significant differences (HSD) correction.

[1] Because every individual was assigned to a class at each wave they participated in, the sample size at level 2 is $3 \times 205 + 2 \times 48 + 39 = 750$ (since 205 individuals participated in all three waves, 48 individuals participated in two waves, and 39 individuals participated in only one wave).

Results

Descriptive Statistics

Descriptive statistics for the ER strategies per wave are presented in Table 1, and correlations between the mental health outcomes (wave 3) are provided in Table 2.

Model Selection

In the first step, we identified the different occasion-level profiles (accounting for the nested structure at the wave level, while assuming that the profiles were consistent across waves). Table 3 displays the fit indicators for one to ten profiles. The BIC scores decreased with model

Table 1 Descriptive statistics for the emotion regulation strategies and affect by EMA wave

	Wave 1			Wave 2			Wave 3		
	M (SD)	% Zero responses	ICC	*M (SD)*	% Zero responses	ICC	*M (SD)*	% Zero responses	ICC
Reappraisal	2.58 (2.03)	52.2%	.41	2.48 (2.09)	58.45%	.43	2.23 (1.91)	61.5%	.44
Distraction	2.66 (2.09)	51.7%	.43	2.58 (2.15)	56.59%	.41	2.32 (1.98)	59.8%	.39
Self-comp	2.74 (1.99)	45.5%	.54	2.58 (2.13)	56.76%	.39	2.34 (1.99)	59.4%	.37
Expression	2.55 (2.03)	53.8%	.45	2.36 (1.98)	59.25%	.46	2.36 (2.03)	61.0%	.42
Social sharing	2.42 (2.04)	58.6%	.41	2.41 (2.06)	59.87%	.47	2.26 (1.97)	61.9%	.43
Rumination	2.73 (2.15)	51.2%	.43	2.49 (2.08)	57.91%	.50	2.41 (2.03)	58.4%	.43
Suppression	2.81 (2.20)	49.6%	.42	2.52 (2.12)	57.18%	.48	2.37 (2.03)	58.8%	.42
Negative affect	1.87 (1.14)	39.7%	.47	1.79 (1.11)	47.1%	.55	1.78 (1.13)	43.38%	.64
Positive affect	5.12 (1.64)	3.1%	.51	5.21 (1.62)	2.6%	.53	5.06 (1.66)	2.85%	.60

Self-comp = self-compassion; Presented descriptives were calculated across all assessments and participants. ICC = intraclass correlation, reflects the proportion of between-person variance. The column '% Zero responses' represents the overall proportion of occasions at which participants reported not to have used a specific emotion regulation strategy

Table 2 Descriptive statistics and correlations between the mental health outcomes at wave 3

	1	2	3	4	5	6
1. Depression	-					
2. Anxiety	.68**	-				
3. Loneliness	.47**	.40**	-			
4. Emo eating	.46**	.36**	.24**	-		
5. NA	.47**	.34**	.29**	.27**	-	
6. PA	-.42**	-.34**	-.39**	-.23**	-.51**	-
M (SD)	1.50 (.49)	1.97 (.48)	2.91 (.32)	1.68 (.75)	1.77 (.91)	5.05 (1.29)

Emo = emotional; NA = negative affect; PA = positive affect

* $p < .05$ ** $p < .01$

Table 3 Model fit statistics for LPA models with different numbers of level 1 profiles (and one level 2 Class)

N of profiles	LL	Number of parameters	BIC	BIC Change	Entropy (L1)	CE (L1)	Smallest AvePP (L1)	Size smallest *P*
1	−534292.90	14	1068678.48	-	1	-	-	-
2	−472430.38	22	945006.40	123672.08	.94	.02	.98	.37
3	−459402.73	30	919004.06	26002.34	.92	.04	.87	.21
4	−447850.16	38	895951.88	23052.18	.94	.03	.94	.09
5	−440154.30	46	880613.12	15338.76	.96	.02	.92	.06
6	**−431094.79**	**54**	**862547.08**	**18066.04**	.94	.04	.91	.06
7	−425841.60	62	852093.65	10453.43	.95	.03	.87	.06
8	−422205.94	70	844875.29	7218.36	.95	.03	.88	.03
9	−417746.39	78	836009.15	8866.14	.97	.02	.93	.03
10	−415418.66	86	831406.64	4602.51	.81	.27	.87	.04

LL = log-likelihood; BIC = Bayesian information criterion; L1 = Level; CE = classification error; AvePP = average posterior class probability; P = emotion regulation profile on the occasion level. Bold indicates the selected model complexity. The six-profile solution demonstrated a larger drop in BIC values than the five-profile solution, while seven to ten-profile solutions demonstrated smaller drops in BIC values. Entropy values, classification errors, and average posterior class probability were consistent until the tenth profile solution. Importantly, compared with solutions with fewer profiles, the six-profile solution provided distinct and theoretically meaningful ER profiles, rather than minor variations of previously identified profiles. Therefore, based on statistical criteria, and especially theoretical interpretability and alignment with prior findings (Grommisch et al., 2020), six profiles were selected at Level 1 in the first step. To verify whether the profiles remained consistent across the three waves, step 1 was also conducted separately for each wave (see Tables S1-S3 for fit indices in Supplementary Information). The results revealed that a 6-profile solution provided good fit for each wave. Notably, the profiles remained consistent across waves, supporting the assumption of profile stability.

In the second step, we identified the number of person-level classes, while fixing the number of occasion-level profiles to six. The BIC values continued to decrease with increasing number of classes but showed diminishing improvements beyond the three-class solution (BIC drop = 2083.65). The entropy also decreased with higher class solutions (from 0.98 to 0.96). The smallest average posterior probability (average posterior class probability = 0.996) and the smallest class size (0.15; 15% of the sample) of the three-class solution reflected good classification accuracy and interpretability. Adding a fourth class did not provide meaningful theoretical distinctions, leading to the selection of three classes. Table 4 displays the fit indicators for one to seven classes.

In the third step, we reassessed the number of Level-1 profiles by comparing models that included three person-level (Level-2) classes and varying numbers of occasion-level (Level-1) profiles. The purpose of this step was to assess whether the optimal number of Level-1 profiles varied with the number of Level-2 classes. Table 5 presents the fit coefficients for a series of ML-LPA models with three Level-2 classes and up to ten Level-1 profiles. Similar to step 1, the six-profile solution demonstrated a larger drop in BIC values than the five-profile solution, while seven to ten-profile solutions demonstrated smaller drops in BIC values. Regarding classification quality at Level-1—evaluated using entropy R-squared, classification error, and average posterior class probability—the model with six Level-1 profiles consistently performed good. Consequently, we selected the model with six occasion-level ER profiles and three person-level classes as the final model.

Table 4 Model fit statistics for LPA models with different numbers of level 2 classes (and six level 1 Profiles)

Number of classes	LL	Number of parameters	BIC	BIC change	Entropy (L2)	CE (L2)	Smallest AvePP (L2)	Size smallest C
1	−431094.80	54	862547.08	-	-	-	-	-
2	−419412.21	60	839221.62	8565.50	.99	.003	1.00	.50
3	**−416837.61**	**66**	**834112.15**	**2083.65**	.98	.01	.99	.15
4	−414996.49	72	830469.62	1195.46	.99	.01	.99	.12
5	−413952.95	78	828422.27	730.38	.98	.01	.98	.09
6	−413115.88	84	826787.84	573.41	.97	.02	.98	.09
7	−412720.24	90	826036.29	479.48	.97	.02	.98	.07

LL = log-likelihood; BIC = Bayesian information criterion; L2 = Level 2; CE = classification error; AvePP = average posterior class probability; C = emotion regulation class on the person level. Bold indicates the selected model

Table 5 Model fit statistics for LPA models with different numbers of level 1 profiles (and three level 2 Classes)

N of profiles	LL	Number of parameters	BIC	BIC Change	Entropy (L1)	CE (L1)	Smallest AvePP (L1)	Size smallest *P*
1	−534292.90	16	1068691.72	-	1	-	-	-
2	−460807.55	26	921787.22	146904.50	.95	.01	.98	.39
3	−446283.74	36	892805.81	28981.41	.93	.03	.95	.13
4	−434579.42	46	869463.37	23342.44	.95	.02	.95	.09
5	−426304.17	56	852979.06	16484.31	.95	.03	.92	.11
6	**−416837.61**	**66**	**834112.15**	**18866.91**	.95	.03	.93	.06
7	−411062.11	76	822627.34	11484.81	.96	.03	.92	.06
8	−406261.53	86	813092.39	9534.95	.96	.03	.92	.05
9	−400439.66	96	801514.84	11577.55	.97	.02	.92	.04
10	−399943.92	106	800589.58	925.26	.96	.03	.91	.03

LL = log-likelihood; BIC = Bayesian information criterion; L1 = Level; CE = classification error; AvePP = average posterior class probability; P = emotion regulation profile on the occasion level. Bold indicates the selected model

Can Different Latent Profiles of Emotion Regulation Be Identified (Occasion-Level)

Figure 2 displays the conditional means for each ER strategy per profile, with profiles ordered by size (i.e., in descending order of number of occasions assigned to this profile). Of the six profiles, two profiles showed similar levels for each ER strategy, but differed in intensity of usage. We labeled them *no-ER* profile (P1; 51.31% of occasions), and *multi-ER (moderate)* profile (P2; 12.11%). The *multi-ER (moderate)* profile was characterized by a moderate use of all strategies including reappraisal, distraction, engagement, self-compassion social support, rumination, and suppression, suggesting that adolescents in this profile engaged in a moderate but not intensive use of all ER strategies within emotional episodes. The other four profiles differed qualitatively in composition (i.e., the intensity of specific strategy usage): one profile was characterized by moderate use of suppression and rumination, and lower use of reappraisal, social support and distraction (*low adaptive* profile; P3; 11.74%); one profile was characterized by higher use of putatively adaptive strategies, and moderate use of rumination and suppression (*high adaptive* profile; P4; 9.64%); one profile was characterized by higher use of distraction, moderate use of suppression and lower use of social support (*internalizing ER* profile; P5; 8.95); a last profile was characterized by higher use of social support, moderate use of engagement (i.e., expression), and lower use of distraction (*externalizing ER* profile; P6; 6.25%).

Can Different Latent Classes of Emotion Regulation Be Identified (Person-Level)

Figure 3 displays the different person-level classes. Overall, most adolescents tended to have a strong preference for one or two repertoire profiles. Some adolescents (41.10%) belong to a predominantly multi-ER (moderate) + low adaptive class (C1), as they most often selected a mix of ER profiles, including both moderate adaptive and less adaptive strategies. Others (35.62%) fall into a predominantly no-ER class (C2), frequently choosing a no-ER profile and rarely engaging in other strategies. A smaller group (23.29%) belongs to a predominantly high adaptive class (C3), consistently selecting profiles characterized by strong use of adaptive ER strategies.

Are Strategy Repertoires Associated with Mental Health?

Means and standard deviations of the mental health outcomes for the different classes of adolescents are displayed in Table 6. The corresponding figures are reported in the

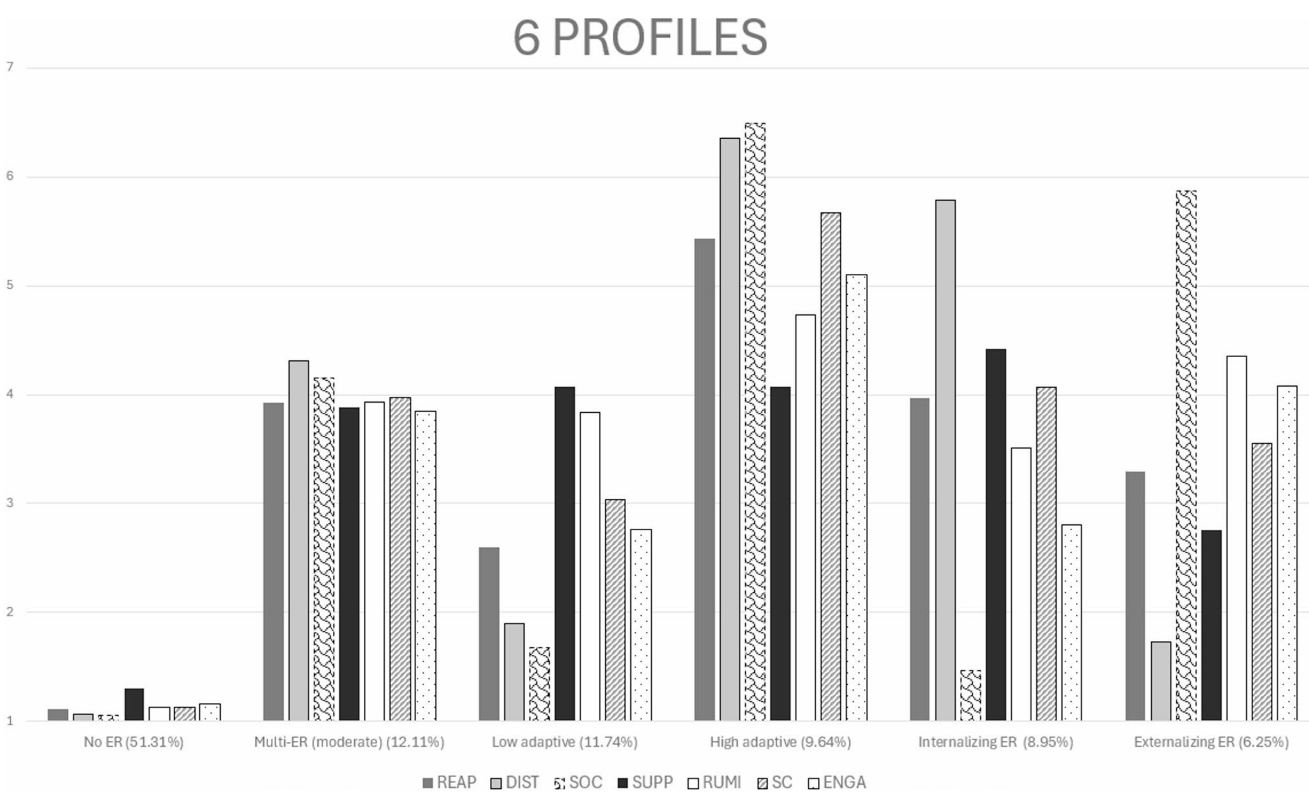

Fig. 2 Overview of Occasion-Level Profiles. *Note*. REAP = cognitive reappraisal; DIST = distraction, SOC = social support; SUPP = suppression; RUMI = rumination; SC = self-compassion; ENGA = engagement; ER = emotion regulation

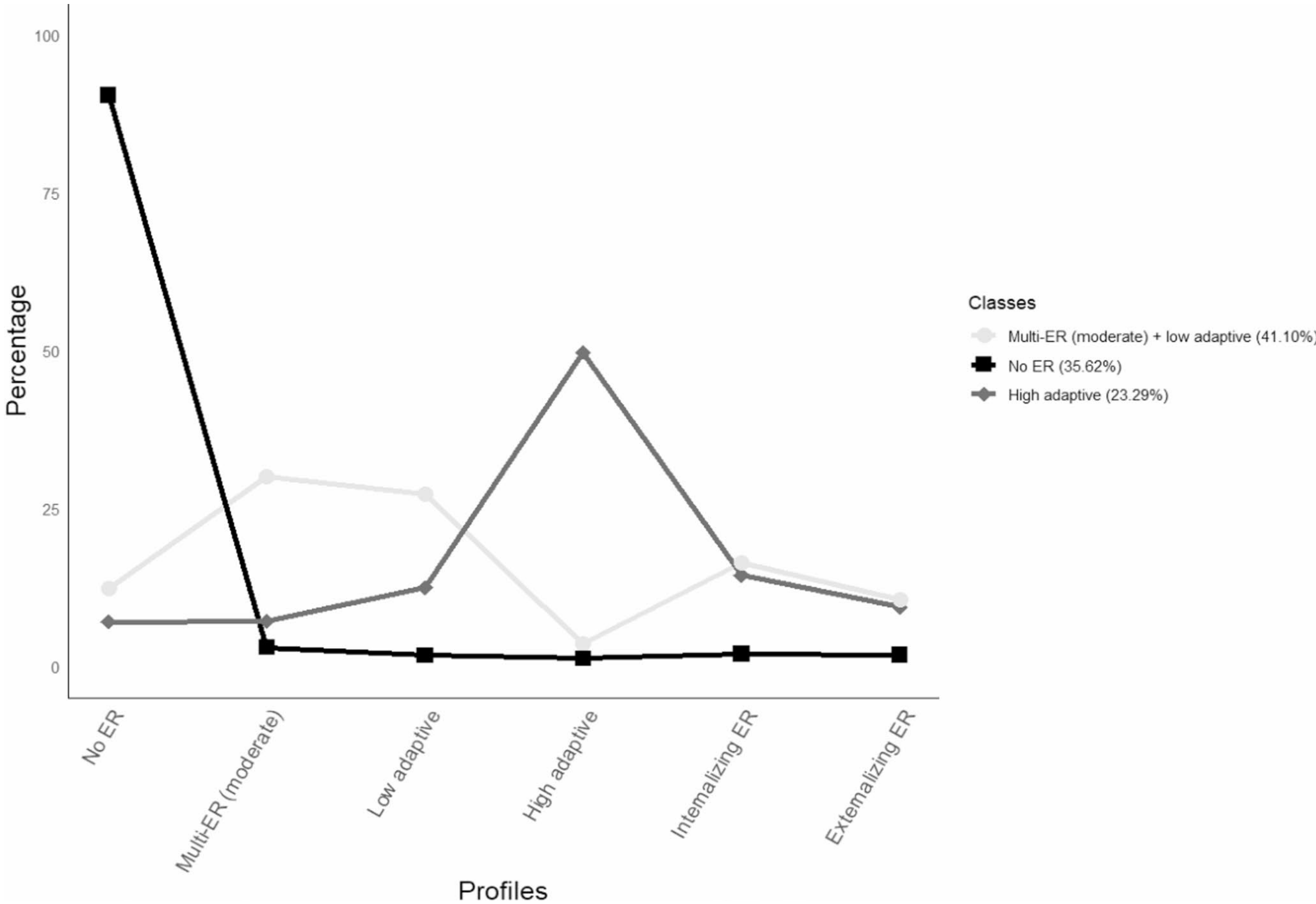

Fig. 3 Overview of Person-Level Classes. *Note*. DIST = distraction; SOC = social support; ER = emotion regulation

Table 6 Descriptive statistics of mental health outcomes (wave 3) per class

	C1: Multi-ER (moderate) + Low adaptive	C2: No-ER	C3: High adaptive	F-test	*p*-value
Depression	1.60 (0.51)[a]	1.38 (0.45)[b]	1.51 (0.47)[ab]	4.61	.01
Anxiety	2.03 (0.53)[a]	1.88 (0.47)[a]	1.98 (0.40)[a]	2.36	.10
Loneliness	1.92 (0.70)[a]	1.71 (0.54)[a]	1.71 (0.59)[a]	3.37	.04
Emotional eating	1.74 (0.74)[a]	1.56 (0.72)[a]	1.78 (0.80)[a]	1.17	.17
Negative affect	2.12 (0.99)[a]	1.27 (0.38)[b]	1.89 (0.98)[a]	23.87	<.01
Positive affect	4.64 (1.33)[a]	5.41 (1.25)[b]	5.22 (1.09)[b]	9.01	<.01

ER = emotion regulation; *F*-test is the overall test for differences across classes. A statistically significant *F*-test without differing superscripts (e.g., Loneliness) indicates that while the omnibus test was significant, no pairwise differences were significant after adjustment. Superscripts with different letters in a row denote significant mean differences between classes (adjusted p <.05 based on Tukey's Honest Significant Difference test). Superscripts sharing at least one letter do not differ significantly (e.g., for depression, C3 does not differ from C1 or C2)

Supplementary Information (Figures S1-S6). The overall *F*-tests indicated that the mean differences in anxiety symptoms and emotional eating were not statistically significant (p =.10 and p =.17, respectively). However, statistically significant differences among the latent classes were observed for depressive symptoms (p =.01), loneliness (p =.04), negative affect (p <.01), and positive affect (p <.01). Consequently, pairwise comparisons (with Tukey HSD for multiple testing) were conducted for these mental health outcomes (see Table 6).

The results revealed that participants in the no-ER class (C2) showed lower levels of depressive symptoms compared to the multi-ER (moderate) + low adaptive class (C1) ($p_{adjusted}$ < 0.01). Additionally, we found that participants belonging to the no-ER class (C2) reported lower levels of negative affect than the participants in the high adaptive class (C3) ($p_{adjusted}$ < 0.01), and the multi-ER (moderate) + low adaptive class (C1) ($p_{adjusted}$ < 0.01). Additionally, we found that participants in the no-ER class (C2) reported higher levels of positive affect than participants in the multi-ER (moderate) + low adaptive class (C1) ($p_{adjusted}$ = 0.02). Similarly, participants in the high adaptive class (C3) reported more positive affect than participants in the multi-ER (moderate) + low adaptive class (C1) ($p_{adjusted}$ < 0.01). The other comparisons between the classes were not significant or became not significant after applying the Tukey HSD correction for multiple testing.

Exploratory Analyses

Exploratory analyses were conducted to examine whether background characteristics (i.e., ethnicity, sex, family structure) or emotion intensity differed across the three ER classes. We found no significant relations with background variables, such as family structure (all p >.49). However, the classes differed significantly in the intensity of the reported negative emotion ($F(2) = 33.27$, p <.01). Post-hoc comparisons indicated that adolescents in the no-ER class reported lower emotional intensity compared to those in the multi-ER (moderate) + low adaptive class ($p_{adjusted}$ < 0.01) and the high adaptive class ($p_{adjusted}$ < 0.01) (see Figure S7).

Discussion

Using a person-centered approach across three waves of EMA data, the current study examined adolescents' strategy repertoires in daily life and their associations with internalizing symptoms and social-emotional distress. Consistent with our first research question, we identified six distinct occasion-level ER profiles, ranging from minimal use (*no-ER* profile) to moderate use of all ER strategies, including specific combinations such as the *high adaptive* profile. These findings align with prior adult research, underscoring the diversity of ER usage and the importance of assessing a range of strategies (Grommisch et al., 2020; Guassi Moreira et al., 2024). Notably, 51.13% of adolescents reported no ER strategy use, a rate five times higher than the one previously identified in adults (Grommisch et al., 2020). Methodological differences across studies (e.g., EMA timing and survey design) may play a role. However, this may also reflect adolescents' ongoing development of ER capacities and emotional awareness (Schweizer et al., 2020). During early adolescence, rapid neurobiological changes occur, that are associated with heightened affective reactivity alongside still-maturing top-down control systems (Dahl et al., 2018; Somerville et al., 2010). Such developmental asynchrony may make it harder for early adolescents to identify or deliberately use specific ER strategies, contributing to lower reported ER use. At the same time, many adolescents in this class simply might not have experienced unpleasant emotions requiring regulation during the sampled periods, rather than lacking regulatory capacity.

Additionally, we identified three person-level classes representing the variability (or lack thereof) in the use of ER profiles over EMA occasions. Specifically, the first class was characterized by multi-ER usage (moderate level but lower adaptive), the second by no ER strategy usage, and the final one by high usage of traditionally adaptive strategies. This finding is consistent with prior research in adults and adolescents that also found large groups of individuals who consistently relied on a single profile (e.g., between 35% and 50%) (De France & Hollenstein, 2017; Grommisch et al., 2020; Lougheed & Hollenstein, 2012).

Consistent with our second research question but contrary to our hypothesis, we found that adolescents in the no-ER class reported the lowest levels of depressive and anxiety symptoms, and the highest levels of daily positive affect. Conversely, adolescents belonging to the multi-ER (moderate level but lower adaptive) class tended to report higher levels of depressive and anxiety symptoms, and lower levels of positive affect. The high adaptive class displayed a mixed pattern, with higher positive affect similar to the no-ER group but higher negative affect resembling the multi-ER group. Overall, these findings contrast with previous research in community-based samples of adults, where low ER usage was generally associated with more depressive and anxiety symptoms, and the experience of more negative affect and fewer positive affect (Grommisch et al., 2020; Guassi Moreira et al., 2024). The high adaptive class in this study reported higher positive affect than the multi-ER (moderate level but lower adaptive) group, aligning with prior adult studies (Grommisch et al., 2020; Guassi Moreira et al., 2024).

One explanation is that adolescents in the no-ER class may not have needed regulation due to low stress or negative affect. This aligns with broader evidence that the adaptiveness of ER depends not only on repertoire size but also on the context-sensitive application of strategies, such that individuals may benefit more from using fewer strategies when situational demands are low (Aldao et al., 2015; Bonanno & Burton, 2013). In line with this interpretation, the exploratory analyses showed that adolescents in this class reported significantly lower emotion intensity than those in the multi-ER (moderate) + low adaptive and high adaptive classes, while no differences emerged for background characteristics (e.g., ethnicity, gender, family structure). Alternatively, some ER may have gone unreported due to unconscious or unassessed strategies like acceptance (Yeager et al., 2022) or implicit regulation (Gyurak et al., 2011). Thus, classification in the no-ER group may reflect lower need or unmeasured automatic regulation. This explanation would suggest that ER strategy use reflects both availability and situational demands.

Implications for Future Research

Overall, this study provides new insights into how adolescents' ER repertoires relate to mental health, expanding existing research on adults. The findings emphasize that the composition of strategy repertoire might be particularly beneficial for mental health. Notably, adolescents with a wide range of strategies (i.e., multi-ER [moderate]) did not differ in mental health outcomes compared with other groups in ways that would suggest that a larger repertoire is inherently beneficial, although we cannot determine the directionality of this association due to the correlational nature of this study.

The study also suggests that adolescents in the no-ER class reported generally better mental health. One possible interpretation, consistent with descriptive patterns of lower negative emotion intensity and prior literature on context-sensitive ER (e.g., Blanke et al., 2022), is that these individuals may have had lower situational demand for ER strategies. However, we cannot determine causality, and it remains possible that their limited ER use reflects differences in regulatory capacity rather than solely situational need. Overall, these findings underscore the need for research to move beyond measuring repertoire size and instead examine how individuals combine basic ER skills, such as acceptance, with putatively adaptive and maladaptive strategies across emotional contexts (i.e., composition). Future longitudinal studies should explore how ER repertoires evolve with adolescent development, and how strategy profiles change depending on contextual factors (Kalokerinos & Koval, 2024).

Limitations

The main strengths of the present study lie in the use of three waves of EMA data in a cohort of adolescents. Nonetheless, several limitations bear noting. First, although pooling three EMA waves strengthened the robustness of our findings, it may also have obscured age-related changes, given that ER can develop markedly over short periods in early adolescence (Dahl et al., 2018; Somerville et al., 2010). Second, single items were utilized to assess the different ER strategies, a choice aimed at reducing participant burden. While this approach aligns with earlier EMA studies (Brans et al., 2013; Lennarz et al., 2019) and the items were derived from a validated EMA measure (Medland et al., 2020), it may impact the reliability of the measures, particularly for more complex constructs like cognitive reappraisal.

Third, only seven ER strategies were assessed to capture ER repertoires. This was done to ease participant burden. Many other strategies, such as acceptance, mindfulness, or problem-solving, could have been included to offer a more comprehensive understanding of adolescents' ER patterns. The exclusion of these strategies may have restricted the depth of the findings and the ability to fully explore the diversity of ER repertoires.

Next, repertoire size and composition were examined without considering the context-sensitive use of ER strategies (Kalokerinos & Koval, 2024). While some individuals may use strategies flexibly according to the situation, others might apply them without a good strategy-situation fit, potentially affecting mental health outcomes (Werner et al., 2025). Additionally, our focus was limited to ER in response to negative emotions. Future research should explore how adolescents regulate positive emotions, which may involve distinct strategies and serve different developmental functions (van Roekel et al., 2024). A final limitation is that model selection criteria (such as information criteria and class separation indices) did not always clearly favor a single model, with two or more models performing similarly well. Therefore, the model was partially selected based on theoretical considerations. This is common in LPA (Grommisch et al., 2020; Masyn, 2013), which complicates the determination of the optimal model. Despite following guidelines to identify the best-fitting model, this ambiguity in model selection could influence the interpretation and robustness of the findings. Additionally, determining the meaning and labels for the latent profiles and classes can be a subjective process, and different individuals might interpret the same class/profiles differently. This subjectivity may affect the clarity and consistency of the results.

Conclusion

This study identified six occasion-level ER profiles and three person-level classes varying in ER strategy use. Mental health outcomes differed across groups: adolescents in the no-ER class showed the most favorable outcomes, with lower depressive and anxiety symptoms and higher positive affect, whereas those in the multi-ER class reported the poorest. The high adaptive class showed a mixed pattern, characterized by positive affect levels comparable to the no-ER group but negative affect levels similar to the multi-ER group. These findings highlight that ER effectiveness depends not just on the repertoire size but also strategy composition. Future research should examine how specific combinations of strategies support mental health across contexts and test interventions that foster flexible, context-sensitive ER use.

Additional Information

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s42761-026-00354-z.

Competing Interests The authors declare no competing interests.

Availability of Data and Material All data files and code are shared on The Open Science Framework (OSF): https://osf.io/2a7yf/

Authors' Contributions J.B. conceptualized the study, developed the methodology, collected data, performed data analyses, and prepared the original draft. G.D. contributed to methodology, data collection, data analyses, and manuscript reviewing. M.R. contributed to conceptualization, data analyses, and manuscript reviewing. J.G. contributed to conceptualization and manuscript reviewing. K.W. contributed to conceptualization and manuscript reviewing. M.G. contributed to conceptualization, methodology, supervision, and manuscript reviewing. All authors reviewed the manuscript.

Ethics Approval The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Use of Artificial Intelligence (AI) No AI tools were used in the writing of this manuscript.

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