



Patterns of Ongoing Thought Are Associated With Emotion Regulation and Negative Affect in Daily Life

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Abstract

Humans have thousands of thoughts every day—often shaped by personal memories, goals, and environmental cues—that are deeply intertwined with emotional functioning. Yet, it remains unclear how these naturally occurring thoughts relate to people’s ability to dynamically regulate their emotions and their emotional well-being in daily life. To address this question, the present study explored whether and when common patterns of ongoing thought are associated with differences in emotion regulation (ER) variability—the degree of moment-to-moment change in the use of different regulatory strategies—across individuals and settings, as well as negative affect in everyday life. Over seven days, 120 participants completed 3,286 experience sampling surveys assessing ongoing thoughts, ER variability, and negative affect in real-world contexts (data collected in 2023–2024). Principal components analysis identified common “thought patterns,” which were then used to predict participants’ ER variability and negative affect. One thought pattern—characterized by negative, intrusive, and distractive content—was associated with lower ER variability and heightened negative affect, as captured by higher levels of anxiety, stress, and loneliness. Importantly, the link between this thought pattern and negative affect was moderated by momentary ER variability. Social activities, such as texting or engaging in conversations, similarly buffered the adverse relationship between this thought pattern and negative affect in daily life. These findings demonstrate how common, recurring patterns of ongoing thought relate to both ER variability and emotional well-being, underscoring the potential protective role of social interactions and variable use of diverse regulatory strategies from our ER repertoire.

Keywords Adaptive cognition · Self-generated thoughts · Negative affect (loneliness, anxiety, stress) · Experience sampling · Ecological momentary assessments (EMA)

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Introduction

Humans are estimated to generate over 6,000 thoughts daily (Tseng & Poppenk, 2020), with spontaneous, ongoing thoughts like mind wandering occupying more than 40% of waking hours (Killingsworth & Gilbert, 2010; Klinger & Cox, 1987; McVay et al., 2009; Turnbull et al., 2019). These ongoing thoughts are complex, encompassing a mix of unconstrained cognition often influenced by personal memories, goals, and internal states. While some thoughts are loosely connected to sensory input, others are triggered by external stimuli (Andrews-Hanna et al., 2014; Mildner & Tamir, 2019; Poerio et al., 2017; Smallwood & Schooler, 2006, 2015; Wallace et al., 2024).

Ongoing thoughts are often emotionally charged and play a crucial role in everyday mood, decision-making, and emotional functioning (Killingsworth & Gilbert, 2010; Mulholland et al., 2023, 2024; Ruby et al., 2013; Smallwood et al., 2013). Over time, these emotionally laden thoughts can influence mental health outcomes and well-being (Kucyi et al., 2023). For example, a study using experience sampling found that repetitive, negatively valenced, and intrusive thoughts are closely associated with higher levels of depression, anxiety, and stress in daily life (Rosenkranz et al., 2020). Similarly, spontaneous task-unrelated thoughts have been related to more negative emotional experiences in real-world contexts (Mills et al., 2021; Thiemann et al., 2023). Moreover, research combining experience sampling with hormonal assessment found that thoughts characterized by negative and future-oriented content were associated with heightened subjective stress and elevated cortisol levels (Linz et al., 2018), suggesting a detrimental effect of maladaptive future-oriented anticipation on emotional functioning.

Given the well-established link between ongoing cognition and emotional functioning (Andrews-Hanna et al., 2013; Ruscio et al., 2011), surprisingly little is known about how patterns of ongoing thought relate to emotion regulation (ER)—the processes through which individuals influence their emotional experiences and responses. ER not only influences decision-making (Grecucci et al., 2013; Grecucci & Sanfey, 2014; Morawetz et al., 2019, 2020) and behavior (Sheppes, 2020), but also directly impacts both mental and physical health (Aldao et al., 2010; Gross, 2002; Gross & John, 2003; Hu et al., 2014; Rammensee et al., 2023). While traditional ER research tended to classify strategies as adaptive (e.g., cognitive reappraisal to increasing positive affect and reducing negative affect) or maladaptive (e.g., rumination and suppression) (John & Gross, 2004; Richards & Gross, 2000; Srivastava et al., 2009), this dichotomy has been challenged, as it often oversimplifies the nuanced relationship between cognition, contexts, and emotions (Aldao

& Nolen-Hoeksema, 2012; Aldao et al., 2010, 2015; Poerio et al., 2013). Instead, recent advances in affective science highlight a dynamic process perspective, particularly in ER research (Koval et al., 2015; Koval, Brose et al., 2015; Koval, Butler et al., 2015; Koval & Kuppens, 2012). This framework emphasizes the importance of the ability to flexibly adopt different ER strategies based on situational demands and individual characteristics (e.g., current goals) within ever-changing environments. It also examines the conditions under which specific strategies are adaptive (or not) (Aldao et al., 2015; Bonanno & Burton, 2013; Koval et al., 2023).

To capture such dynamics, researchers have begun quantifying moment-to-moment changes in individuals' use of regulation strategies, employing specific metrics such as ER variability. Common indices of ER variability include *between-strategy variability*, which reflects how individuals adjust their choice of strategies from their ER repertoire across different situations or moments, and *within-strategy variability*, which describes adjustments in the degree to which a single strategy is employed across different situations (Aldao et al., 2015; Blanke et al., 2020; Wenzel et al., 2022). Across both metrics, higher ER variability has been associated with lower negative affect, fewer depressive symptoms, and greater well-being (Blanke et al., 2020; Grommisch et al., 2020; Wang et al., 2021). This growing body of evidence suggests that individuals benefit from varying their ER use of strategies in different real-world environments.

Our study examined how common patterns of ongoing thought are associated with real-world ER variability and negative affect. We also explored whether enhanced ER variability can buffer against the negative relationships between thought patterns and negative affect in daily life and identified contexts in which these relationships are most—or least—pronounced. To our knowledge, no prior research has characterized the complex interplay between ongoing thought patterns, ER variability, and negative affect across diverse contexts in everyday life. Gaining a better understanding of these interrelations may help identify factors associated with vulnerability and resilience in daily emotional functioning.

To this end, over seven days, 120 participants completed 3,286 experience sampling surveys assessing their ongoing thoughts, ER strategies, and momentary negative affect in daily life. At each time point, multi-dimensional experience sampling (MDES) captured participants' current thoughts across 16 dimensions (e.g., features of content and temporal focus) (Ho et al., 2020; Konu et al., 2021), the use of 11 ER strategies prior to the survey (Grommisch et al., 2020), and indicators of negative affect, including momentary perceived stress, anxiety, and loneliness (daSilva et al., 2021; Mack et al., 2021). Principal component analysis (PCA) was

used to identify common thought patterns reported in natural environments. These thought patterns we then used to predict ER variability and negative affect in daily life. These analyses also assessed interactions between ER variability and common thought patterns to explore whether variability in ER use (as assessed in within- and between-strategy variability scores) mitigates the relationship between thought patterns and real-world negative affect. Contextual factors such as location, activities, and environmental cues were also evaluated as potential moderators.

By examining associations among thought patterns, ER variability, and negative affect in real-world contexts, our study highlights potential factors linked to emotional functioning and resilience. The results suggest that greater variability in deployment of ER strategies may be less likely to co-occur with certain patterns of ongoing cognition. Moreover, our findings demonstrate how heightened ER variability can mitigate detrimental associations between thought patterns and daily negative affect. More broadly, the findings offer insights that could ultimately inform theoretical models of adaptive cognition and guide interventions aimed at supporting mental health and well-being in daily life.

Method

Participants

To determine the appropriate sample size, we conducted a power analysis using the *simr* package in R (version 4.3.3) (Green & MacLeod, 2016). An initial analysis based on 100 simulations ($\alpha=0.05$) indicated that 110 participants would be sufficient to detect a small effect size ($r = 0.22$, $R^2 = 0.05$) with 94% power (95% CI [88.72, 98.36]). To ensure the robustness of this estimate, we repeated the procedure with 1,000 simulations, which yielded qualitatively similar results (required $N=110$; 94% power, 95% CI [92.79, 95.74]). These calculations were informed by data from a pilot sample ($N=47$) and a linear mixed model approach (preregistration: https://aspredicted.org/C2D_J9Y; preregistration deviations are reported in Table S1). To account for potential dropouts and preregistered exclusions of participants (e.g., due to insufficient experience sampling data in daily life) (Christensen et al., 2003), we recruited 120 participants aged 18–45 (80 female, 40 male, $M_{\text{age}} = 19.66$, $SD_{\text{age}} = 3.76$) from the Queen's University campus (94% of the participants were university students) and local Kingston community through flyer advertisement and the participant pool at the Department of Psychology at Queen's University. Participants self-reported their ethnic backgrounds as follows: Caucasian/White (70%), Asian (16.7%), Multiracial (5.8%), African American/Black (2.5%), Hispanic/Latino (2.5%), and Other (2.5%).

Procedure

Participants first completed an online survey to assess facets of trait well-being (including trait negative affect), followed by a 7-day experience sampling session to assess momentary negative affect in daily life using the phone-based *Samplify* application (Shevchenko et al., 2021). During this one-week period, participants received five randomly timed survey prompts daily, spaced at least two hours apart, between 9:00 a.m. and 9:00 p.m., yielding up to 35 surveys per participant over the study period (Courvoisier et al., 2012; Eisele et al., 2022; Ho et al., 2020; McKeown et al., 2021). On average, surveys took approximately 2 min to complete. Participants were compensated \$5 for completing the initial trait well-being surveys and \$1 for each experience sampling survey submitted. An additional \$10 bonus was provided for completing more than 80% of the surveys (28 out of 35). Overall, participants completed 3,376 surveys (Mean \pm SD: 27.52 ± 7.76 surveys per participant). After excluding surveys with incomplete responses (90 surveys, representing less than 3% of all observations), 3,286 surveys were included in the formal analysis. Other exclusion criteria preregistered—such as surveys completed unusually quickly or with identical responses across all items—did not apply to any of the collected data. All study procedures were approved by the Queen's University Health Sciences and Affiliated Teaching Hospitals Research Ethics Board (HSREB, ethics number: PSYC-267-22), and all participants provided informed consent.

Experience Sampling Survey

Participants received prompts on their phones five times per day for one week, requesting them to complete brief surveys designed to capture their patterns of ongoing thought, emotion regulation strategies adopted since the last prompt, and momentary negative affect in daily life. Below, we outline each of the measures included in the survey.

Patterns of ongoing thoughts (multidimensional experience sampling, MDES) At the beginning of each survey, participants reported the content of their ongoing thoughts immediately preceding the prompt using multidimensional experience sampling (MDES). This was assessed using 16 established dimensions (Table 1), rated on a 10-point Likert scale (Ho et al., 2020; Konu et al., 2021; McKeown et al., 2021; Mulholland et al., 2023). MDES data allowed for the characterization of common thought patterns in daily life using data reduction techniques (see below).

Emotion regulation (ER) strategies Next, participants rated their use of 11 ER strategies to cope with unpleasant

Table 1 Overview of MDES questions used to characterize thought patterns in daily life

Dimension	Question	Response Scale
Focus	My thoughts were focused on an external task or activity	Not at all – Completely
Future	My thoughts involved future events	Not at all – Completely
Past	My thoughts involved past events	Not at all – Completely
Self	My thoughts involved myself	Not at all – Completely
Person	My thoughts involved other people	Not at all – Completely
Emotion	The emotion of my thoughts was	Negative – Positive
Image	My thoughts were in the form of images	Not at all – Completely
Word	My thoughts were in the form of words	Not at all – Completely
Sound	My thoughts were in the form of sound	Not at all – Completely
Detailed	My thoughts were detailed and specific	Not at all – Completely
Deliberate	My thoughts were	Spontaneous – Deliberate
Problem	I was thinking about solutions to problems (or goals)	Not at all – Completely
Intrusive	My thoughts were intrusive	Not at all – Completely
Knowledge	My thoughts contained information I already knew (e.g., knowledge or memories)	Not at all – Completely
Absorption	I was absorbed in the contents of my thoughts	Not at all – Completely
Distracting	My thoughts were distracting me from what I was doing	Not at all – Completely

Participant rated their ongoing thoughts on each dimension using a 10-point Likert scale

feelings or situations in the last two hours using a 100-point scale (Table S2) (Grommisch et al., 2020) (“Based on the following statements, please rate how you dealt with the unpleasant feelings and situations in the last two hours”). We focused our ER items on regulating unpleasant feelings for two reasons: (i) ER is more frequently deployed to manage negative than positive affect in daily life, maximizing measurement sensitivity and ecological validity; and (ii) to limit respondent burden under experience sampling constraints while capturing the usage of strategies in naturalistic settings (Brans et al., 2013; English et al., 2017; Heiy & Cheavens, 2014; Vanderlind et al., 2022). The raw data were then rescaled to range between 0 and 6 for formal analysis (Blanke et al., 2020; Wenzel et al., 2022). These strategies were selected to comprehensively represent different stages of the process model of ER (Gross, 1998, 2013, 2015). The battery included strategies related to situation selection (“I

chose which situation to put myself in”), situation modification (“I actively changed something in the situation”), attentional deployment (“I did something to distract myself physically or mentally”), cognitive change (“I changed the way I was thinking about the situation”) and response modulation (“I was careful not to express my emotions to others”), to name a few. These self-reports were used to calculate two indicators of ER variability per participant: between-strategy variability and within-strategy variability (see below).

Momentary negative affect To assess indicators of momentary negative affect and well-being in real life, participants rated their perceived loneliness, anxiety, stress, and social/emotional support right before the survey probe (daSilva et al., 2021; Mack et al., 2021) on 5-point Likert scales (“To what degree have you felt...”; “Not at all – Extremely”). These socio-affective measures were integrated into a momentary negative affect score at each measurement point (see below).

Contextual information Participants also reported contextual information for each survey prompt, including their location, activity, and social environment (multiple choice, Table 2), following previous experience sampling studies (Ho et al., 2020; Konu et al., 2021; McKeown et al., 2021; Mulholland et al., 2023). This data was used to identify contextual factors that attenuated (or heightened) the link between patterns of ongoing thoughts, ER variability, and momentary negative affect in daily life.

Trait negative affect and well-being surveys In addition to our primary measures of momentary negative affect in daily life, participants also completed a battery of established questionnaires to capture variance in trait negative affect and other facets of well-being (4.43 ± 4.20 days before the experience sampling session). See Table S3 for a summary of all questionnaires. Data from the questionnaire battery served as supplemental data to examine the generalizability of the associations between ongoing thoughts in daily life and variance in (trait vs. state) negative affect and well-being.

Analysis

Analyses of Experience Sampling Survey Data

Patterns of ongoing thoughts (principal component analysis, PCA) To identify common patterns of ongoing thought in daily life, we used MDES data from all participants and observations ($N=3,286$) together with principal component

Table 2 Overview of contextual information collected during experience sampling in daily life

Item	Questions	Response Options (Multiple Choice)
Location	Where were you?	Inside a home Inside a shop Inside a workplace Inside (other): please specify here Outside in a city or town Outside in nature Outside (other): please specify here
Activity	What were you doing?	Eating Homework Household chores Listening to music Napping or resting Nothing or waiting Personal exercise Personal hygiene care Physical leisure or sports Reading Shopping Pets Talking in person Talking on the phone Texting by phone Traveling or commuting Using a computer or an electronic device Walking the dog Watching TV Working (paid or volunteer) Other activity: please specify here
Environment (Physical)	Were you alone, or <i>physically</i> with other people?	Alone Around people but not interacting with them Around people and interacting with them
Environment (Virtual)	Were you alone, or <i>virtually</i> with other people?	Alone Around people but not interacting with them Around people and interacting with them

analysis (PCA), following previously established procedures (Ho et al., 2020; Konu et al., 2021; McKeown et al., 2021; Mulholland et al., 2023; Wang et al., 2018). The PCA was implemented in Python (version 3.8.8) using the *Scikit-learn* (Pedregosa et al., 2011) and *Scipy* packages (Virtanen et al., 2020). MDES data were z-scored using *Scipy* before the PCA. To assess the suitability of the MDES data for PCA, we used the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Next, we implemented a PCA with Varimax rotation to decompose the MDES data to maximize the distinctiveness of each solution (Ho et al., 2020; Konu et al., 2021; McKeown et al., 2021; Mulholland et al., 2023; Wang et al., 2018). The loadings from components with an eigenvalue above 1 were retained for further analyses to predict ER variability and

momentary negative affect in daily life from common patterns of ongoing thought (see below).

ER variability (moment level and person level) To characterize people's ER variability in daily life, we computed two established global indicator variables (Blanke et al., 2020): between-strategy variability and within-strategy variability.

Between-strategy variability refers to the use of one or several strategies from a battery of strategies at a given time, reflecting a prioritization of certain strategies. This measure is calculated at the level of each observation (moment level) and can be averaged across all moment-level scores of a participant (person level). Between-strategy variability was calculated in the following way: At observation t , individual i reported the usage of L ($L=11$) ER strategies s (Table S2) on a 100-point rating scale (rescaled to 0–6 for formal analysis to consistent with previous established studies (Blanke et al., 2020; Wenzel et al., 2022), yielding L values x_{sti} . Thus, values of x_{sti} indicate the usage of strategy s reported by individual i at moment t . These values enabled calculating the average across all x_{sti} (M_{between} ; between-strategy mean, also referred to as mean endorsement) (Eq. 1) (Wenzel et al., 2022) and the relative standard deviation (RSD_{between}) at time t (Mestdagh et al., 2018). Values of $RSD_{\text{between}(it)}$ represent the between-strategy variability of a particular participant i at time t (which we refer to as moment level in the result section). The code for the estimation of RSD values is available here (https://ppw.kuleuven.be/okp/software/relative_variability/) (Mestdagh et al., 2018). To aggregate data at the person level, all moment-level between-strategy variability scores for an individual i were averaged across all observations obtained for that participant.

$$M_{(\text{between})\,ti} = \frac{1}{L} \sum_{s=1}^L x_{sti} \quad (1)$$

Within-strategy variability refers to variation in the intensity of usage of a particular strategy over time or contexts (as captured in different observations). Thus, high scores in this measure suggest that this strategy is used in some contexts, but not others, suggesting discriminative use of that strategy over time. *Within*-strategy variability can only be calculated at the person level as follows: for each strategy s , individual i reported the usage of that particular strategy across N observations throughout the weeklong experience sampling session. For each strategy, we then calculated a person's average intensity of usage of that strategy across time (Eq. 2, M_{within}) as well as the relative standard deviation (RSD_{within} , using the same R-based code as for RSD_{between} ;

see above). To calculate each individual's overall within-strategy variability, the 11 strategy-specific RSD_{within} values were averaged (person level).

$$M_{(within) i} = \frac{1}{N_i} \sum_{t=1}^{N_i} x_{ti} \quad (2)$$

Note that we used the relative standard deviation (RSD) compared to standard deviation (SD) used in earlier seminal work on ER variability (Blanke et al., 2020) to account for concerns that ER variability indices are confounded by the mean endorsement of ER strategy use, especially when the response is bounded (Mestdagh et al., 2018). The relative standard deviation (RSD) was proposed as a solution, and researchers have replicated the association between ER variability and negative affect using this modified ER variability index (Wenzel et al., 2022).

Momentary negative affect (moment level and person level) During the one-week experience sampling period, participants repeatedly rated their perceived level of loneliness, stress, anxiety, and social/emotional support in daily life. Between-person and within-person (Bakdash & Marusch, 2017) intercorrelations among each item are presented in Table S4. Following prior work (Blanke et al., 2020; Wenzel et al., 2022) and our preregistration, momentary negative affect at each timepoint was computed by averaging loneliness, stress, and anxiety. Diverging from our preregistration, social/emotional support was excluded from the composite score because of the low or non-significant correlations with other items of momentary negative affect (Table S4; see Table S1 for a complete list of preregistration deviations; supplemental analyses confirmed that results remained qualitatively unchanged when social/emotional support was included in the negative affect composite score). The aggregated momentary negative affect scores served as the primary variable of interest in subsequent analyses examining the association with ongoing thoughts and ER variabilities in daily life. Higher composite scores indicate greater momentary negative affect in daily life. In addition to the moment-level scores, we also computed person-level averages (mean across all moment-level values obtained for an individual) for supplemental analyses.

Analyses of trait negative affect and well-being (person level) In addition to state-like measures of momentary negative affect in daily life (experience sampling), we also characterized variance in individuals' *trait* negative affect and other facets of well-being using a battery of 13

questionnaires (Table S3). To this end, we first applied PCA for data reduction following previous studies (Wang et al., 2018). The analytical steps matched those described for the thought pattern decomposition (see above). PCA-based latent variables were used to characterize individual differences (person level) in trait negative affect, social resilience, and social well-being. The trait questionnaire data allowed the investigation of the correspondence between trait- and state-like indices of participants' negative affect and well-being (Pearson correlations using the *cor_test* function as implemented in R version 4.3.3). More importantly, these data were used to examine the generalizability of the association between ongoing thoughts, ER variability, and trait (vs. state) negative affect and well-being.

Predicting ER variability and negative affect in daily life from ongoing thought patterns

To examine the association between ongoing thoughts, emotion regulation (ER) variability and negative affect in daily life, we used linear mixed-effects models (LMMs). The models were fitted using the *lme* function from the *nlme* package (Pinheiro et al., 2017), specifying an autoregressive (AR1) structure to account for temporal autocorrelation between repeated assessments within individuals. We included age and sex (1=female and 0=male) as fixed-effects covariates, and participant ID and day number were included as random effects to account for the nested nature of the data (moments within days within participants). LMMs are widely used to study real-world dynamics of ongoing thought patterns (Konu et al., 2021; McKeown et al., 2021; Mulholland et al., 2023; Turnbull et al., 2019). To evaluate the effect sizes, we calculated the $R^2_{adjusted}$, reflecting the variance explained by the independent variables.

Model 1 examined whether common patterns of ongoing thought were associated with ER variability in daily life. Values of between-strategy ER variability at each observation served as the dependent variable. The loadings for common thought patterns (derived from the PCA) served as predictor variables. The model simultaneously estimated within-person and between-person effects of common thought patterns through person-mean centering of predictors: the within-person effect (moment-level values) represents deviations from an individual's own average thought pattern at a given moment, while the between-person effect (person-mean centered values) represents differences in average thought patterns across individuals. The model also included the mean ER endorsement (between-strategy mean) as a fixed effect (Blanke et al., 2020; Wenzel et al., 2022) to control for the overall intensity of ER strategy usage at each timepoint. The inclusion of this regressor was motivated by our

supplemental findings of significant associations between ongoing cognition and overall ER strategies use (Table S5).

Model 2 examined whether patterns of ongoing thought predict momentary negative affect in daily life. The model matched the one described above, but momentary negative affect served as the dependent variable (instead of between-strategy ER variability). For descriptive purposes, within- and between-person correlations among all primary variables used in Models 1 and 2 are reported in the supplemental material (Table S6).

For exploratory purposes, we also ran time-lagged versions of the above two models (reported in the supplemental material) to examine whether ongoing thought patterns at one timepoint predicted subsequent ER variability (Model 1a) and momentary negative affect (Model 2b) in daily life. Specifically, to create the lagged predictors, we ordered each participant's observations by time t and examined whether changes in ongoing thought at time t predict changes in ER variability (or negative affect) at time $t + 1$. This helps assessing temporal order (i.e., whether fluctuations in one variable tend to precede changes in another in time), which is a necessary—but not sufficient—condition for causality. Thus, the results of these supplemental analyses provide insights into potential directionality, though not causal inference.

Based on the results of Models 1 and 2, another supplemental post-hoc Model 3 further examined the predictive role of ongoing thoughts and ER variability for momentary negative affect in real-world settings. This LMM included between-strategy ER variability (moment level) and its interaction with a specific thought pattern (Component 2: negative intrusive and distracting thoughts) as predictor variables. To probe and visualize the interaction effect, a simple slopes analysis was conducted using the *interactions* package in R (version 4.3.3) (Long & Long, 2019).

Model 4 explored how context shapes the relationship between ongoing thoughts and negative affect in daily life. Momentary negative affect served as the dependent variable. Categorical contextual variables (Table 2) and their interaction with thought pattern 2 (negative intrusive and distracting thoughts) served as predictor variables.

In addition to the LMMs specified above, we also run a series of general linear models (GLMs) using the *lm* function as implemented in R version 4.3.3 (Bates et al., 2015; Kuznetsova et al., 2017; Core Team, 2013) to examine whether we can use common thought patterns to predict (1) *within-strategy ER variability* (which can only be calculated at the person level, dependent variable), and (2) *trait negative affect*, as captured in trait questionnaires (compared to state-like measures of momentary negative affect in daily life assessed in experience sampling data) and other aspects of trait well-being.

Results

This section begins by introducing the key measures used to address our main research questions, along with descriptive statistics where applicable. These measures include common thought patterns in daily life (MDES data), indices of emotion regulation (ER) variability—capturing both between- and within-strategy variability—and measures of negative affect at both momentary and trait levels. We then address our central research questions: Are patterns of ongoing thought associated with changes in ER variability (Model 1) and negative affect in daily life (Model 2)? Can ER variability buffer the association between maladaptive thought patterns and negative affective (Model 3)? Finally, how do real-world contexts modulate the relationship between thought patterns and negative affect (Model 4)?

Common thought Patterns in Daily Life (PCA of MDES Data)

First, we identified common patterns of ongoing thought in daily life. We applied PCA with Varimax rotation to all thought data generated from responses to the 16 MDES questions ($N=3,286$ observations across participants). The Bartlett's test of sphericity was significant, $\chi^2(120)=7572.7$, $p<0.001$, suggesting that the correlations between variables were sufficiently large for PCA. The Kaiser-Meyer-Olkin measure indicated a good level of sampling adequacy ($KMO=0.78$). These results confirmed the appropriateness of using PCA for our dataset.

We identified four principal components with eigenvalues above 1 that accounted for 46% of the total variance in MDES data (Figure S1). PCA loadings (Table S7) from the four components were used to generate thought word clouds (Fig. 1). We named the four components based on the MDES dimensions that dominated their composition and labels of previously identified patterns of ongoing thought in real life (Mulholland et al., 2023). Component 1 (20% of variance) was labelled "*detailed task focus*" due to high positive loadings on dimensions "detailed," "deliberate," "problem," and "(task) focus." Component 2 (11% of variance) was labelled "*negative intrusive distracting*" due to high loadings on these three dimensions. Component 3 (8%) was labeled "*episodic social cognition*" as this thought pattern was characterized by high loadings on the dimensions "past," "(other) person," "(positive) emotions" in various modalities ("image," "sounds," and "words"). Component 4 (7%) was labeled "*future self*" due to high loadings on these two dimensions. Henceforth, we will use these labels to discuss the link between common patterns of thought with ER variability and negative affect (well-being). However, we acknowledge that other labels could be applied

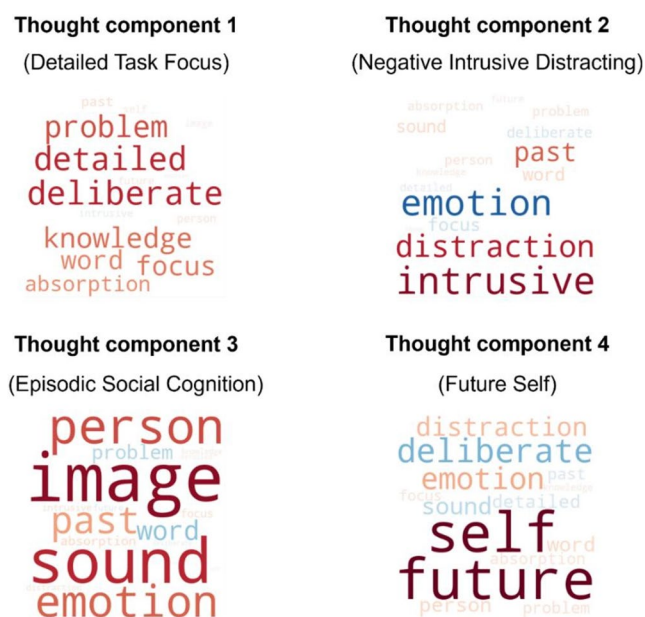


Fig. 1 Common patterns of ongoing thought in daily life. Word clouds illustrate the item loadings of the four common thought patterns in real life (3,286 observations; PCA on the 16-dimensional MDES data summarized in Table 1). Word size represents the strength of loadings of the MDES items (Table S7), with larger fonts indicating a stronger association between the item and component. Word color indicates the direction of the relationship (red=positive loadings, blue=negative loadings)

to the four components. Note that the four decomposed thought patterns closely match those identified in previous work on ongoing cognition in daily settings (Mulholland et al., 2023), speaking towards their reliability and generalizability. The histograms of the identified thought patterns are presented in Figure S5.

Robustness checks To further understand the robustness and reliability of the identified common thought patterns in real life, we conducted a series of supplemental analyses. First, we estimated the split-half reliability of our identified components of ongoing thought. To this end, we split our MDES data into two random samples. We then tested how the components estimated in each half of the data (using the PCA approach outlined above) related to each other by computing the mean correlation between the corresponding principal components identified in each dataset. Both subsamples indicated a 4-component solution (based on eigenvalues above 1) and produced reliable components, with an average similarity score of $r=0.96$ (range of 0.92 to 0.98) (see Figure S2).

Second, we estimated a 4-component PCA solution using oblique rotation (instead of Varimax rotation) of all MDES data (see Table S8 for the component loadings) and compared it to the solution generated using Varimax rotation (Table S7). This supplemental PCA yielded similar

components, with high similarity between corresponding components (range of $r=0.9976$ to 0.9998) (Figure S3). In this study, we focused on PCA solutions derived using Varimax rotation for consistency with prior research using similar methods (Konu et al., 2021; McKeown et al., 2023; Mulholland et al., 2023).

Overall, the results of these supplemental analyses demonstrate the robustness and reliability of the patterns of ongoing thoughts in daily life used to test our main research question: Can we predict variance in ER variability and negative affect (well-being) in daily life from patterns of ongoing thoughts?

ER variability in daily life We first confirmed that participants utilized a broad range of strategies to regulate their emotional experience in daily life (for an overview of strategy-specific endorsements, see Figure S6; for examples of individual profiles of ER strategy use over the 7-day experience sampling period, see Figure S7). Next, for each participant, we estimated several indicators of their ER variability in daily life: between-strategy variability (estimated at the moment level and person level; overall $M\pm SD$: 0.47 ± 0.13), mean ER endorsement (moment and person level; 2.79 ± 0.85), and within-strategy variability (person level only, 0.49 ± 0.20). Histograms of between- and within-strategy variability scores are provided in Figure S5. Taken together, we found considerable variance in our measures of ER variability to explore in our main analyses.

Negative affect in daily life For each timepoint (experience sampling survey), we estimated aggregate scores of momentary negative affect ($M\pm SD$: 2.20 ± 0.59). Mean scores for individual items were as follows (5-point scale): stress= 2.41 ± 1.17 ; anxiety= 2.22 ± 1.12 , loneliness= 1.94 ± 0.57 , and social/emotional support= 2.75 ± 1.21 . Notably, social/emotional support was not included in the negative affect composite score, as it showed weak or non-significant correlations with the other negative affect items (Table S4), representing a deviation from our preregistration. The data showed people experienced considerable levels of negative affect in their daily lives, with sufficient variance to justify our main analyses.

Trait negative affect and well-being (PCA of questionnaire data, person level) Patterns of ongoing thoughts and momentary negative affect in the real world were both assessed during daily experience sampling surveys. Thus, it's possible that shared method variance and/or mere temporal proximity drive the functional link between both concepts. To assess the generalizability of the thought-negative affect relationship, we also assessed people's trait negative affect (and other aspects of trait well-being) using a battery

of established questionnaires before the daily experience sampling period. Table S3 provides an overview of the descriptive statistics of each item assessed in this battery.

To characterize latent dimensions of trait negative affect and other aspects of trait well-being in this supplemental analysis, we used PCA with Varimax rotation on these questionnaire data (120 observations). The Bartlett's test of sphericity was significant, $\chi^2(66)=742.74$, $p<0.001$, and the KMO measure of sampling adequacy (0.83) indicated that the data were appropriate for PCA. The first three orthogonal components (eigenvalues >1) accounted for more than 65% of the total variance (Table S9, Figure S4). Component 1 (42% of explained variance, labeled "trait negative affect") was dominated by measures of negative affect, anxiety, and depression. Component 2 (16% of explained variance, labeled "social resilience") was characterized by high negative loadings on resilience, well-being, positive affect, and perceived social support. Component 3 (8% of explained variance, labeled "social well-being") was characterized by positive loadings on social contacts (network size) and negative loadings on loneliness. These component loadings were used as dependent variables in the supplemental analyses that tested if common thought patterns in daily life (person level) also predict *trait* negative affect, social resilience or social well-being (see below). We also calculated the bivariate correlation between the three component scores of trait well-being (including trait negative affect) and items used to characterize momentary negative affect in daily life (Table S10), demonstrating the significant association between momentary negative affect in daily life (experience sampling) and trait negative affective (trait questionnaires), $r=0.45$, $p<0.001$, FDR corrected.

Thought Patterns are Associated with ER Variability in Daily Life (Model 1)

Between-strategy variability of ER. Having all the key measures in place, we now turn to addressing our key questions. We first examined whether ongoing thought patterns were associated with fluctuations in emotion regulation (ER) variability, as reflected in moment-to-moment indices of between-strategy variability. The model simultaneously estimated within-person and between-person effects of common thought patterns (achieved through person-mean centering of predictor variables). The within-person effects represent momentary deviations from an individual's own average thought tendencies, while between-person effects capture differences in average thought tendencies across individuals. The model explained a substantial amount of variance ($R^2_{\text{adjusted}} = 0.26$).

We found that within-person fluctuations of thought pattern 2 ("negative intrusive distracting") were significantly

associated with fluctuations of between-strategy variability in ER use ($b = -0.01$, $SE = 0.002$, $t(2987.23) = -2.74$, $p = 0.006$, 95% CI = $[-0.01, -0.002]$). Thus, fewer negative intrusive and distracting thoughts were associated with an enhanced moment-by-moment ability to regulate emotions in a more variable manner. We also identified a positive association of thought pattern 1 ("deliberate task focus") with between-strategy variability ($b = 0.01$, $SE = 0.002$, $t(2957.32) = 4.02$, $p < 0.001$, 95% CI = $[0.004, 0.013]$). Thus, having relatively more thoughts directed towards the ongoing task was linked to a more variable use of different ER strategies. No other thought pattern was associated with between-strategy ER variability at the within-person level (Table 3).

At the between-person level, participants who reported fewer negative intrusive and distracting thoughts (thought pattern 2) on average tended to show greater between-strategy variability, $b = -0.14$, $SE = 0.02$, $t(116.12) = -8.74$, $p < 0.001$, 95% CI = $[-0.17, -0.11]$ (for an illustration, see Fig. 2A). Similarly, participants with higher scores on thought pattern 4 ('future self') displayed greater between-strategy variability, $b = 0.06$, $SE = 0.02$, $t(114.95) = 2.46$, $p = 0.01$, 95% CI = $[0.01, 0.10]$. No other thought pattern was significantly related to between-strategy ER variability at the person level (Table 3). However, these associations were not observed in supplemental time-lagged analyses (Table S11).

Within-strategy variability of ER. We next tested whether individual differences in thought patterns were also associated with within-strategy ER variability, which captures the

Table 3 Patterns of ongoing thought are associated with between-strategy ER variability

Predictor	Estimate (SE)	95% CI	t	p
<i>Within-person effects</i>				
TP1	0.01 (0.002)	[0.004, 0.013]	4.02	<0.001
TP2	-0.01 (0.002)	[-0.01, -0.002]	-2.74	0.006
TP3	0.001 (0.002)	[-0.003, 0.005]	0.15	0.88
TP4	<0.001 (0.002)	[-0.006, 0.004]	-0.40	0.68
<i>Between-person effects</i>				
TP1	0.03 (0.02)	[-0.01, 0.06]	1.54	0.13
TP2	-0.14 (0.02)	[-0.17, -0.11]	-8.74	<0.001
TP3	-0.01 (0.02)	[-0.04, 0.02]	-0.41	0.68
TP4	0.06 (0.02)	[0.01, 0.10]	2.46	0.01
<i>Control Variables</i>				
Mean endorsement	-0.02 (0.004)	[-0.03, -0.01]	-4.51	<0.001
Age	<0.001 (0.003)	[-0.01, 0.004]	-0.33	0.74
Sex	0.02 (0.02)	[-0.024, 0.06]	0.80	0.43

TP thought pattern, SE standard error, CI confidence interval, Thought patterns 1 = "detailed task focus," 2 = "negative intrusive distracting," 3 = "episodic social cognition," 4 = "future self."

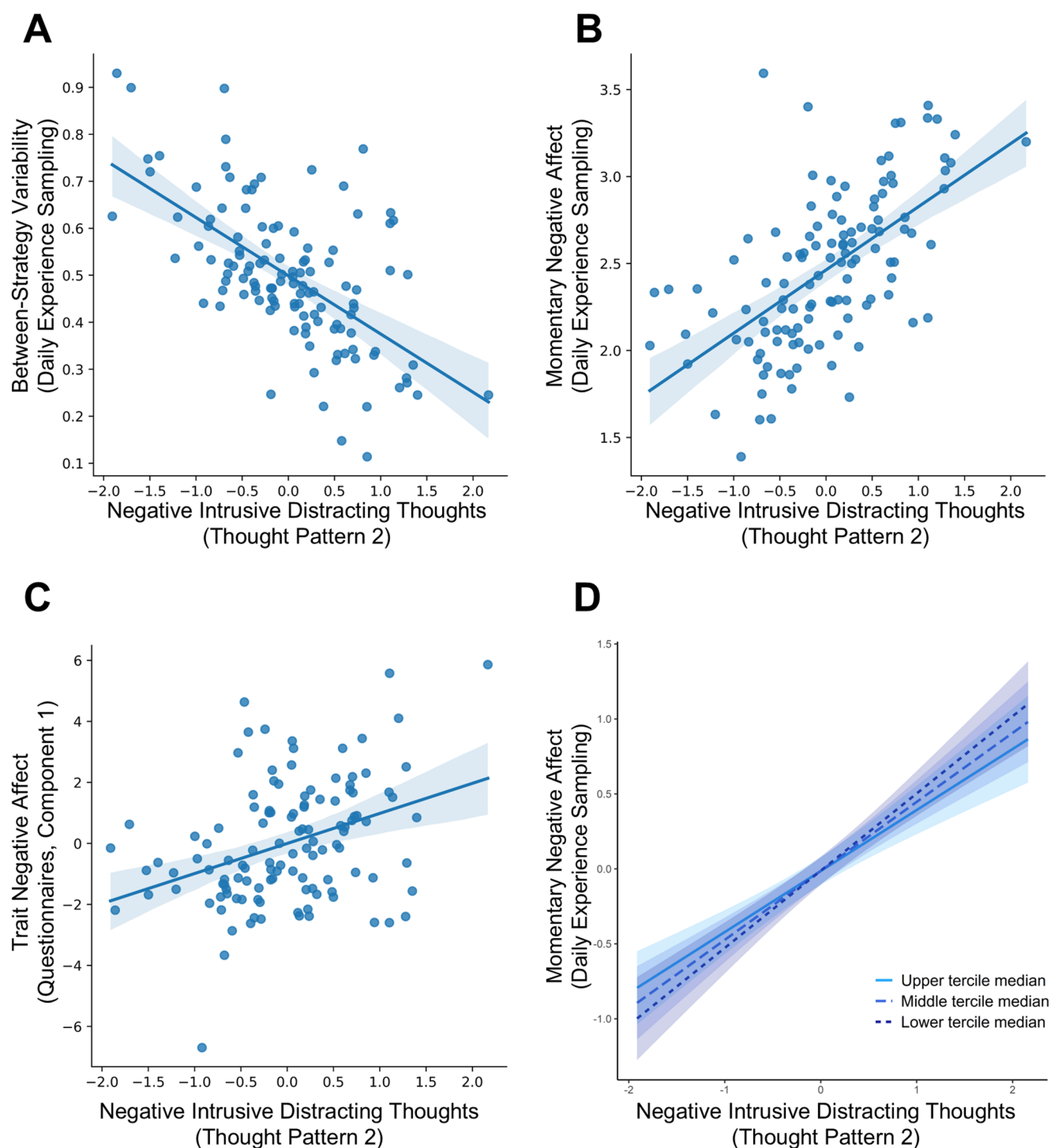


Fig. 2 Associations between a common thought pattern, emotion regulation (ER) variability, and (state and trait) negative affect. **(A)** Fewer negative intrusive and distracting thoughts (thought pattern 2) are associated with more variable ER usage in daily life (higher between-strategy ER variability; $R^2_{\text{adjusted}} = 0.50$). **(B)** More negative intrusive and distracting thoughts are linked with greater *momentary* negative affect in the real world (indexed by higher anxiety, loneliness, and stress; $R^2_{\text{adjusted}} = 0.46$). **(C)** The same thought pattern is also associated with higher *trait* negative affect (PCA component 1

of questionnaire data; $R^2_{\text{adjusted}} = 0.18$). **(D)** ER variability moderates the association between this thought pattern and momentary negative affect. Individuals who use a more variable range of ER strategies (high between-strategy variability) show a weaker positive association between negative intrusive and distracting thoughts and momentary negative affect in daily life (interaction: $b = -0.82$, $SE = 0.26$, $t(112) = -2.10$, $p = 0.002$, 95% CI = $[-1.34, -0.31]$, $R^2_{\text{adjusted}} = 0.18$). All panels depict between-person effects

extent to which people vary the intensity of a specific ER strategy across different situations (can only be computed at the person level). The model explained a modest-to-moderate amount of variance ($R^2_{\text{adjusted}} = 0.24$). Consistent with the findings for between-strategy variability reported above, participants reporting fewer negative intrusive and distracting thoughts (thought pattern 2) tended to show greater within-strategy ER variability ($b = -0.08$, $SE = 0.02$, $t(111) = -5.15$, $p < 0.001$, 95% CI = $[-0.12, -0.05]$). No other thought pattern was significantly associated with this index of ER variability (Table S13).

Taken together, these results indicate that negative intrusive and distracting thought tendencies co-occur with reduced variability in ER strategy use across time and contexts. This association emerged consistently across both between- and within-strategy indices of ER variability and across analyses at the momentary and person levels of ongoing thoughts.

Thought patterns are associated with negative affect in daily life (Model 2)

Next, we examined the relationship between ongoing thought patterns and momentary negative affect in daily life. The model simultaneously estimated within-person and between-person effects of common thought patterns on negative affect in daily life. The model explained a moderate proportion of variance in the outcome variable, $R^2_{\text{adjusted}} = 0.22$.

Consistent with our earlier findings, momentary increases in thought pattern 2 (“negative intrusive distracting”) were associated with higher levels of negative affect at the within-person level ($b = 0.19$, $SE = 0.01$, $t(3064.41) = 20.29$, $p < 0.001$, 95% CI = $[0.17, 0.21]$). In other words, when individuals experienced more negative intrusive and distracting thoughts than usual for them, they also reported greater momentary negative affect. In addition, fluctuations in thought pattern 1 (“deliberate task focus”) and thought pattern 3 (“episodic social cognition”) were significantly related to momentary negative affect ($b = 0.05$, $SE = 0.01$, $t(3048.49) = 6.59$, $p < 0.001$, 95% CI = $[0.04, 0.07]$; $b = -0.08$, $SE = 0.01$, $t(3039.69) = -8.48$, $p < 0.001$, 95% CI = $[-0.10, -0.06]$, respectively; Table 4).

At the between-person level, participants who, on average, reported more negative intrusive and distracting thoughts (thought pattern 2) also tended to experience higher overall negative affect ($b = 0.42$, $SE = 0.05$, $t(3064.41) = 8.06$, $p < 0.001$, 95% CI = $[0.32, 0.53]$). No other thought pattern showed a significant relationship with momentary negative affect at the between-person level (Table 4).

Finally, a supplemental time-lagged analysis revealed that higher levels of thought pattern 2 (“negative intrusive

Table 4 Patterns of ongoing thought are associated with momentary negative affect in daily life

Predictor	Estimate (SE)	95% CI	t	p
Within-person effects				
TP1	0.05 (0.01)	[0.04, 0.07]	6.59	<0.001
TP2	0.19 (0.01)	[0.17, 0.21]	20.29	<0.001
TP3	-0.08 (0.01)	[-0.10, -0.06]	-8.48	<0.001
TP4	0.01 (0.01)	[-0.01, 0.02]	0.56	0.58
Between-person effects				
TP1	0.04 (0.06)	[-0.10, 0.13]	0.62	0.53
TP2	0.42 (0.05)	[0.32, 0.53]	8.06	<0.001
TP3	-0.09 (0.05)	[-0.19, 0.01]	-1.73	0.08
TP4	-0.02 (0.08)	[-0.18, 0.12]	-0.34	0.73
Control variables				
Mean endorsement	-0.05 (0.02)	[-0.09, -0.02]	-2.95	0.003
Age	<0.001 (0.01)	[-0.02, 0.02]	0.18	0.85
Sex	0.06 (0.07)	[-0.1, 0.2]	0.83	0.41

TP thought pattern, SE standard error, CI confidence interval, Thought patterns: 1 = “detailed task focus,” 2 = “negative intrusive distracting,” 3 = “episodic social cognition,” 4 = “future self.”

distracting”) predicted increased negative affect at the subsequent sampling occasion, suggesting that fluctuations in maladaptive thought patterns precede short-term increases in negative affect (Table S12). This temporal pattern provides preliminary—but not definitive—evidence for a potential causal influence of thought patterns on affective experience.

Overall, these results suggest that negative intrusive and distracting thought patterns are reliably linked with higher negative affect in daily life, both within individuals over time and across individuals on average.

Supplemental Analyses: Association of thought Patterns with Negative Affect at the Item and Trait Level

Prediction of momentary loneliness, stress, and anxiety (experience sampling data, item scores). First, post hoc analyses confirmed that the thought-based association with momentary negative affect in real life was not driven by one particular variable of the aggregate score. Figure S8 illustrates the positive relationship between thought pattern 2 (“negative intrusive distracting”) and increased momentary anxiety, loneliness, and stress in daily life (all p 's < 0.001), suggesting that this thought pattern is associated with various aspects of momentary negative affect in daily life.

Trait negative affect (questionnaire data, person level). Next, we examined whether patterns of ongoing thoughts in daily life are also associated with variance across people's trait negative affect (and other facets of trait well-being),

as captured in established questionnaires completed before the real-world experience sampling session ($M \pm SD$: 4.43 ± 4.20 days). To this end, we completed a series of three GLMs that predicted variance in decomposed trait scores (three components from a PCA on questionnaire data, see Table S9) from thought patterns (person level) (Table S14, between-person level).

Trait negative affect (component 1). Matching results for predictions of momentary negative affect in daily life, we found that thought pattern 2 (“negative intrusive distracting”) was associated with higher *trait* negative affect, as captured in component 1 of the questionnaire data, $b = 1.09$, $SE = 0.24$, $t(112) = 4.60$, $p < 0.001$, 95% CI = [0.62, 1.56], $R^2_{adjusted} = 0.18$ (Fig. 2C). Interestingly, thought pattern 3 (“episodic social cognition”) was negatively associated with negative *trait* affect ($b = -0.67$, $SE = 0.24$, $t(112) = -2.80$, $p = 0.006$, 95% CI = [-1.14, -0.20]) (Table S14). In other words, people who experience frequent thoughts characterized as positive, about the past and others (e.g., positive, past interactions with other people) showed lower levels of *trait* negative affect.

Social resilience (component 2). Thought pattern 1 (“deliberate task focus”) was negatively associated with “social resilience” as captured in PCA component 2 of the questionnaire data, $b = -0.86$, $SE = 0.27$, $t(112) = 3.22$, $p = 0.001$, 95% CI = [-1.39, -0.33], $R^2_{adjusted} = 0.1$. Thought pattern 4 (“future self”) predicted higher social resilience, $b = 0.73$, $SE = 0.36$, $t(112) = 2.04$, $p = 0.04$, 95% CI = [0.02, 1.44]. In other words, people who perceived themselves as more resilient and socially supported tended to report more ongoing cognition characterized by less deliberate task focus and more simulations of one’s future self.

Social well-being (component 3). We also found a significant positive association between thought pattern 3 (“episodic social cognition”) and the “social well-being” component, $b = 0.42$, $SE = 0.18$, $t(112) = 2.25$, $p = 0.02$, 95% CI = [0.04, 0.78], $R^2_{adjusted} = 0.02$. These results indicate that people with larger social networks and lower self-reported loneliness (items that loaded heavily on the social well-being component) tended to think more about positive past interactions with others. No other significant effects were observed (Table S14).

ER Variability Modulates the Link between Ongoing thoughts and Negative Affect in Daily Life (Model 3)

So far, we have shown that negative, intrusive and distracting thoughts are associated with both ER variability (between- and within-variability) and negative affect in real-world settings. This functional link was robust irrespective of whether indicators of ER variability reflect moment- or person-level measures and state- or trait-like measures

of negative affect. However, ER-variability and negative affect are not considered independent. In the current analysis, we indeed found that between-strategy variability explained variance in negative affect at both the person and moment levels (person level: $b = -0.83$, $SE = 0.27$, $t(115) = -3.10$, $p = 0.002$, 95% CI = [-1.36, -0.30]; moment level: $b = -0.24$, $SE = 0.10$, $t(3135.20) = -2.42$, $p = 0.01$, 95% CI = [-0.44, -0.05]), replicating prior findings (Blanke et al., 2020; Wang et al., 2021; Wenzel et al., 2022). Building on this evidence linking more variable usage of ER strategies with reduced negative affect, we next tested for interactions between ER variability and negative intrusive thoughts (thought pattern 2) in predictions of people’s negative affect in daily life. Simply put, we examined if people’s ability to adopt more variable ER strategies modulates the link between thought pattern 2 and negative affect. This post-hoc analysis focused on thought pattern 2 (“negative intrusive distracting”), which showed a robust functional relationship with negative affect.

Negative affect in daily life (moment level) served as the dependent variable; thought pattern 2 (“negative intrusive distracting”), ER variability (between-strategy variability), and their interaction term were used as predictor variables. We found a significant interaction between ER variability and negative intrusive thoughts (within-person level: $b = -0.29$, $SE = 0.11$, $t(2536.44) = -2.50$, $p = 0.01$, 95% CI = [-0.52, -0.06]; between-person level: $b = -0.82$, $SE = 0.26$, $t(112) = -2.10$, $p = 0.002$, 95% CI = [-1.34, -0.31], $R^2_{adjusted} = 0.18$). See Fig. 2D for a visualization of the results of a simple slope analysis and Table S15 for a full list of results. The findings suggest that the functional association between negative intrusive and distracting thoughts and negative affect in daily life was strongest (weakest) for individuals less (more) capable of variably selecting different ER strategies (high between-strategy variability).

Context Modulates the Link between Ongoing thoughts and Negative Affect (Model 4)

Finally, we identified contexts that attenuate (or heighten) the association between negative intrusive thoughts and negative affect in daily life. To this end, we ran a separate model (LMM) that predicted negative affect in daily life (moment level) from thought pattern 2 and its interaction with context information (listed in Table 2). We found that the link between negative intrusive thoughts and negative affect depended on current activities. More specifically, we identified significant negative interactions between the occurrence of the negative intrusive thought pattern and being in conversation, $b = -0.29$, $SE = 0.12$, $t(3114.12) = -2.31$, $p = 0.04$, 95% CI = [-0.53, -0.05], texting with others by phone, $b = -0.55$, $SE = 0.19$, $t(3102.13) = -2.94$,

$p=0.02$, 95% CI = $[-0.91, -0.19]$, $R^2_{adjusted}=0.24$ (Table S16 for full list of results; all p values are FDR corrected). These findings indicate that engaging in meaningful socialization (i.e., texting, conversation) alleviated the detrimental link between negative intrusive thoughts and negative affect in daily life. The participants' location didn't matter (e.g., home, workplace, outside; all p 's > 0.37). Likewise, there were no interactions between the environment and negative, intrusive thoughts (all p 's > 0.56). There were also no 3-way interactions of negative intrusive thoughts, activities (i.e., texting, conversation), and location or environment in a separate post-hoc model (all p 's > 0.11). Thus, for example, the link between thought pattern 2 and negative affect did not differ across virtual or physical environments in which participants interacted with others, or when they were just surrounded by other people (but not interacting with them). Instead, our results suggest that it's meaningful activities related to engaging with others, such as texting or conversation, that might act as a protective factor for the thought-negative affect link identified in our study.

A supplemental post-hoc test found no 3-way interactions between negative intrusive thoughts, ER variability, and context variables (all p 's > 0.06). In other words, the protective effect of meaningful social activities like conversations or texting did not depend on variable ER usage, suggesting that even people with lower ER variability can benefit from this contextual factor.

Discussion

Our minds are continuously engaged in streams of thought, ranging from routine tasks to profound reflections on life and our environment, that are closely intertwined with our emotional experiences. This study investigated how common patterns of ongoing thoughts relate to emotion regulation (ER) variability—defined as the degree to which individuals dynamically vary their use of regulatory strategies across contexts—and the experience of negative affect, including stress, loneliness, and anxiety, in daily life. We identified recurring patterns of thought consistent with prior research (Mulholland et al., 2023), and found that negative, intrusive, and distracting thoughts were linked with both reduced ER variability and heightened negative affect. Supplemental time-lagged analysis further indicated that fluctuations in this thought pattern *preceded* negative affect (but not ER variability), a necessary though not sufficient condition for causal inference regarding the thought–affect association in real-world settings. Importantly, individuals who demonstrated greater variability in their use of ER strategies showed a weaker association between intrusive thought patterns and negative affect, suggesting that ER variability

may serve as a psychological buffer for the thought–affect link. Similarly, social engagement—whether through in-person interactions or virtual communication—attenuated the link between intrusive thoughts and negative affect. While these findings provide exciting new insight into the dynamic interplay between ongoing thought, ER variability, and affective experiences in real life, they remain correlational and cannot exclude the possibility of reverse causation or unmeasured confounding influences. Taken together, the results highlight the protective role of social interactions (Beckes & Sbarra, 2022; Coan & Maresh, 2014; Gross & Medina-DeVilliers, 2020) and variable emotion regulation in mitigating the adverse emotional correlates of intrusive, distracting thinking.

Detrimental and Beneficial Patterns of Ongoing thought for ER Variability

The ability to flexibly deploy diverse strategies to regulate emotions (higher ER variability) is linked to lower negative affect (Blanke et al., 2020; Wang et al., 2021; Wenzel et al., 2022). Yet, the factors that accompany differences in people's ER variability remain poorly explored. Our findings revealed that common thought patterns were systematically associated with ER variability in daily life. More negative, intrusive, and distracting thoughts (across moments and people) were linked to reduced ER variability, across different indicators like between-strategy variability (selecting different strategies from their repertoire) and within-strategy variability (varying the use of a specific strategy across contexts). These findings align with evidence that rumination—persistent, repetitive negative thinking—is associated with heightened psychological distress and poorer mental health outcomes, including depression and anxiety (Aldao et al., 2010). Rumination also mediates the link between chronic stress and psychological health (Zawadzki, 2015), amplifying negative affect and potentially triggering dysregulated coping behaviors (Selby et al., 2008). Conversely, more prospective, self-related (“future self”) thinking was associated with greater ER variability, suggesting that future-oriented cognition co-occurs with more variable ER regulation in everyday life. This evidence is consistent with evidence linking future-oriented thinking with adaptive outcomes, such as enhanced motivation, goal-directed behavior, and improved well-being (Sutin et al., 2023).

While these associations are correlational and cannot establish directionality, they highlight meaningful connections between ongoing cognition and the ability to vary ER strategies in real-world contexts. Future work could experimentally manipulate thought content through interventions such as cognitive behavioral therapy (CBT) or mindfulness-based training to reduce repetitive negative thinking and

foster awareness of intrusive, distracting thoughts (Ashton et al., 2023; Reinecke et al., 2013; Stenzel et al., 2025) or to cultivate adaptive future-oriented cognition (Feruglio et al., 2021). Building on our work, such studies will be crucial to test whether modifying thought processes influences ER variability and, in turn, emotional functioning. Another important direction is to examine potential bidirectional effects, such as whether individuals with greater ER variability subsequently show shifts in ongoing thought content or structure. Together, these findings point toward promising translational opportunities for understanding and potentially improving adaptive emotion regulation and mental health in daily life.

Thought Patterns are Associated with Real-World Negative Affect, Modulated by ER Variability

Negative, intrusive, and distracting thoughts were also linked to reduced state and trait negativity in daily life. This finding aligns with previous research connecting such ongoing cognitive patterns to negative affect captured in the laboratory (Killingsworth & Gilbert, 2010; Konu et al., 2021; Ruby et al., 2013; Smallwood et al., 2009). Importantly, the thought-affect link was observed across multiple markers of negative affect in our data, including perceived levels of loneliness, stress, and anxiety. Given the surge in mental health challenges like depression, anxiety, and loneliness following the COVID-19 pandemic (Santini & Koyanagi, 2021; Schafer et al., 2022; Van der Velden et al., 2021), these results are particularly timely. For example, recent reports suggest that over 20% of people worldwide experience loneliness, which exacerbates other negative emotions such as sadness, worry, and stress (Dugan, 2024; McGrath et al., 2023). Our study offers a potential solution: variable emotion regulation (ER variability) functions as a protective buffer against the adverse link between negative intrusive thoughts, reinforcing its adaptive role (Blanke et al., 2020; Wang et al., 2021; Wenzel et al., 2022). Interventions that cultivate broader ER repertoires and enhance the capacity to vary the application of strategies across contexts could mitigate the negative thoughts-affect link, providing a promising approach to address challenges like the global “loneliness pandemic” (WHO, 2023).

Importantly, our findings also revealed beneficial effects of ongoing thought patterns on other facets of well-being, beyond negative affect, at the trait level. For instance, self-focused prospective thoughts (e.g., reflections on one’s future self) were associated with greater social resilience, including indicators of higher perceived resilience and social support. Similarly, positive reflections on past social interactions (episodic social cognition) correlated with enhanced social well-being, marked by larger social networks and

reduced loneliness. These results align with evidence highlighting the cognitive and emotional benefits of an active, socially integrated lifestyle (Fratiglioni et al., 2004). Promoting episodic social cognition and future-oriented thinking may thus represent valuable strategies to bolster various aspects of well-being, addressing both individual and societal mental health challenges.

Context Modulates the Link between Negative Intrusive thoughts and Negative Affect in Daily Life

Context significantly modulated the thought-affect relationship in daily life, aligning with prior research on the context sensitivity of thought patterns identified through MDES. For instance, earlier studies demonstrated that socializing activities—whether in-person or virtual—shape thought patterns with episodic and social features as well as negative intrusive thoughts (McKeown et al., 2021; Mulholland et al., 2023, 2024). Extending this work, we found that meaningful social interactions, such as conversations or texting, buffered the harmful link between negative intrusive thoughts and daily negative affect, including loneliness, anxiety and stress. Evidence for the efficacy of texting is noteworthy, as digital communication is becoming a popular substitute for face-to-face social interactions and is frequently used for interpersonal ER (i.e., communicating with someone to influence or adjust either your own or their emotional state) (McFarland & Hay, 2023). Interestingly, location (e.g., home, workplace, outdoors) and simply being around others without engaging in social interaction had no such protective effect. Instead, actively participating in social activities emerged as a key factor in mitigating the adverse thought-affect relationship. Notably, this protective modulation effect was independent of ER variability, suggesting that the benefits of social activities generalized across individuals regardless of their abilities to use a variety of ER strategies. These findings underscore the importance of considering the interplay between ongoing cognition (e.g., negative, intrusive thoughts) and context (e.g., activities) in promoting well-being in daily life (Kucyi et al., 2023; Smallwood & Andrews-Hanna, 2013).

Experience Sampling of Ongoing thoughts as a Helpful Tool

Our findings contribute to the growing evidence of the impact of ongoing thoughts on mood and affective states in both laboratory and real-world settings (Konu et al., 2021; Mills et al., 2021; Ruby et al., 2013). By demonstrating the functional link between common thought patterns, ER variability, and real-world negative affect, our results highlight the value of incorporating measures of

ongoing thoughts, such as MDES, into affective and clinical research. Although ecological momentary assessments have gained popularity in recent years (Harari & Gosling, 2023; Koval & Kalokerinos, 2024) and experience sampling has been successfully applied in clinical and sub-clinical populations (daSilva et al., 2021; McGowan et al., 2023; Morawetz et al., 2023), MDES-based assessments of ongoing cognition remain underutilized. Affective states emerge from complex interactions between individual factors (e.g., goals, ER abilities), contexts, and cognition, while simultaneously shaping ongoing thought patterns. MDES data provide a reliable window into this dynamic interplay (McKeown et al., 2025), offering novel insights into how cognition and emotions fluctuate and shape well-being in everyday life. Practically, collecting MDES data through brief smartphone surveys (1–2 min) is cost-effective in terms of time, effort, and financial resources. This approach could enable mental health professionals and other stakeholders to identify at-risk individuals based on daily thought patterns and implement targeted interventions aimed at modifying detrimental or enhancing beneficial thought patterns to improve well-being.

Limitations and Future Directions

Several limitations warrant consideration. First, our sample consisted primarily of young, healthy university students, which limits the generalizability of our findings. Given age-related differences in ER strategy use (Blanchard-Fields et al., 2004; Nolen-Hoeksema & Aldao, 2011) and their neurocognitive bases (Nashiro et al., 2012; Silvers et al., 2017), future work should examine whether these associations replicate in more age- and demographically diverse samples. Second, we focused on 11 strategies derived from the process model of emotion regulation (Gross, 1998, 2013), but additional strategies such as problem-solving (Aldao & Nolen-Hoeksema, 2012; Aldao et al., 2010) or emotion expression (Cameron & Overall, 2018) are also linked to well-being. Future studies could incorporate these as well as positive up-regulation strategies (e.g., savoring, positive reappraisal) to test whether thought patterns differentially relate to down- versus up-regulation processes in daily life. Third, we examined two established indices of ER variability—between- and within-strategy variability. Although variability has been proposed as a prerequisite for flexibility (Aldao et al., 2015), it is not synonymous with it. Our data cannot determine whether variability reflects adaptive, context-sensitive regulation or rather indecisiveness or random fluctuation. Future work should complement variability indices with measures of fit between strategy choice, situational demands, and personal goals to better capture regulatory flexibility and the adaptiveness of ER dynamics.

Finally, and most critically, our analyses were correlational and cannot establish causal relationships between thought patterns, ER variability, and affective outcomes. Nonetheless, the observed associations provide a valuable foundation for hypothesis-driven experimental and longitudinal studies. Future interventions could test whether modifying maladaptive thought content enhances ER variability and emotional well-being in daily life, or conversely, whether cultivating greater ER variability influences the structure and adaptiveness of ongoing thought.

Additional Information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s42761-026-00355-y>.

Conflicts of Interest/Competing Interests The authors declare no competing interests.

Availability of Data and Material We report how we determined our sample size, all inclusion and exclusion criteria, and all measures used in the study. The current study was preregistered (preregistration: [https://aspredicted.org/C2D_J9Y])(https://aspredicted.org/C2D_J9Y). All data and analysis code used in the study are publicly available at the Open Science Framework (OSF; https://osf.io/qmcyw/?view_only=d96f558ff6184503a4a1a3c9efed5193). All analyses were done in R version 4.3.3 (R Core Team, 2013), and Python Version 3.8.8.

Authors' Contributions R.W., A.T., and C.M. designed the study and wrote the main manuscript text. R.W. performed the statistical analysis and created the figures. All authors reviewed, edited, and approved the final version of the manuscript.

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