Between moments, between emotions:

how everyday (in)varying emotional processes relate to social and mental health in adolescents and young adults

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Cover: Erwin Timmerman
Printing: Optima Grafische Communicatie
Layout and design: Optima Grafische Communicatie

ISBN: 978-94-6534-414-0
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Proefschrift ter verkrijging van de graad van doctor
aan de Radboud Universiteit Nijmegen
op gezag van de rector magnificus prof. dr. J.M. Sanders,
volgens besluit van het college voor promoties
in het openbaar te verdedigen op

dinsdag 2 juni 2026
om 16.30 uur precies

door

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Dissertation to obtain the degree of doctor
from Radboud University Nijmegen
on the authority of the Rector Magnificus prof. dr. J.M. Sanders,
according to the decision of the Doctorate Board
to be defended in public on

Tuesday, June 2, 2026
at 4:30 pm

by

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General Introduction

GENERAL INTRODUCTION

1.1 Overview

Emotions are dynamic. We rarely experience the exact same emotions as the hours pass. Emotions change when contexts change: whether we are relaxed at a cafe or irritated at the workplace, lonely when alone or joyful when socializing, and bored while commuting on a train or energetic while jogging in a park. Emotions also change as we influence them through what is known as emotion regulation (Gross, 2015). Facing unpleasant circumstances, we may choose to do nothing, to look for silver linings, or to take action to change the situation we are in. Emotions and regulation together form a continuous, ongoing, and dynamic process (Hollenstein et al., 2013).

In this dissertation, I study the dynamics of emotions and emotion regulation in adolescents and young adults. I refer to these individuals collectively as young people. Adolescence and young adulthood are periods of change. During these years, young people go through puberty and brain maturation while facing academic, social, and vocational transitions (Holmbeck et al., 2006; Koolschijn & Crone, 2013). Young people encounter emotional challenges: negative emotion intensity heightens and fluctuates more rigorously (Bailen et al., 2019; Reitsema et al., 2022; Zimmermann & Iwanski, 2014). At the same time, young people undergo emotional development. Their emotional vocabulary expands, while emotions become more self-referent and grounded in internal experience rather than in external context (Grosse & Streubel, 2024; Nook et al., 2020). Young people's ability to clearly articulate emotional experiences may dip temporarily in middle adolescence before improving again as they enter adulthood (Nook et al., 2018). During this window of both challenge and opportunity, it is crucial for young people to regulate their emotions, especially negative ones (Sisk & Gee, 2022). Difficulties in regulating negative emotions can increase vulnerability to poor social health (e.g., loneliness) and mental health (e.g., psychopathology such as depression and anxiety) (Aldao et al., 2016; McLaughlin et al., 2011; Preece et al., 2021; Silvers, 2022). Therefore, the dynamics of emotions and the associated emotion regulation in young people's daily lives not only reflect how they react to situations and respond to emotions in the short term, but may shape their long-term social and mental health (Aldao et al., 2010, 2015; English et al., 2012; Lakhtakia et al., 2024).

A key aspect theorized to link emotions and their regulation is emotion differentiation, or put simply, knowing what one feels. When young people can make sense of what they feel by distinguishing the intensity across types of emotions, they are informed by their emotions to choose the right type of emotion regulation for the situation (Aldao et al., 2015; Kashdan et al., 2015). This process involves both the intensity and type of emotions (Gross & Jazaieri, 2014; Kuppens & Verduyn, 2015). The intensity of emotions is our yardstick for significance. Emotion intensity informs us how much we care about a context and whether we should act on it (Frijda, 2016; Greenberg, 2006; Schwarz & Clore, 1983). The type of emotions qualitatively informs how we experience the current context (e.g., "I feel bored reading on and don't even want to flip to the next page.") and prepares us to respond to the context in an emotion-specific manner (Frijda, 2016). In parallel, emotion regulation also varies in intensity and type. The type of emotion regulation refers to the strategy of emotion regulation, such as reappraisal (e.g., "It may get better soon. Let's read on.") or distraction (e.g., "Let's watch Netflix for a while before reading on"), which differ in mechanisms and their effects in influencing emotions (Aldao et al., 2010). The intensity in emotion regulation refers to how strongly someone engages with a strategy (Blanke et al., 2022).

Despite the fact that dynamics of emotion and emotion regulation must be considered in both intensity and type, these dynamics have mostly been studied only in terms of how their intensity changes (e.g., T. Sun et al., 2025; see review by Reitsema et al., 2022) in two ways: (a) by considering the intensity change in a single type of emotion or a single emotion regulation strategy (e.g., how intensely someone has been thinking of the silver linings to regulate negative emotions, e.g., Hiekkaranta et al., 2024), or (b) by considering the change in average intensity across types (e.g., mean intensity across multiple types of negative emotions e.g., Blanke et al., 2020). Changes in types of emotions and emotion regulation were rarely studied (e.g., as someone thinks of the silver linings in a sad event, does his sadness transition into other emotions, like hope?), which is plausibly because of the lack of a suitable methodology. If dynamics of emotion and emotion regulation were like piano music, current research can be described as focusing only on the loudness (intensity) but not on which keys (types) on a piano are played. Without considering changes in types, there is no melody, and the dynamics in emotion and emotion regulation are incomplete.

Therefore, in this dissertation, I seek to deepen the understanding of type-related dynamics of emotion and emotion regulation in young people's daily lives. The overarching aim is to demonstrate how type-related dynamic indices of emotion and emotion regulation are related to short-term emotion outcomes (Chapters 2, 3, 4 and 5) and long-term social and mental health (Chapter 5). To do this, I analyzed the data young people have reported hour by hour in their daily lives, where they naturally experience and influence their emotions. I began by examining the theorized notion that knowing one's emotions helps one regulate their emotions. Specifically, I tested whether emotion differentiation, which refers to the distinctiveness in labelling emotions, precedes changes in emotion regulation strategies (emotion regulation variability) and outcomes in terms of emotion intensity (Chapter 3). In asking this differentiation-regulation research question, I realized that the emotion regulation subfield lacked the methodology to detect a theorized change process in emotion regulation, namely switching between emotion regulation strategies. To tackle this, I introduced Bray-Curtis dissimilarity, a method from ecology.

Using this method, I studied how emotion regulation variability is related to negative emotion intensity shortly afterward (Chapter 2). I further applied the new methodology to study how transitions between negative emotions (e.g., from anger to sadness) accompany short-term reductions in overall intensity of negative emotions (Chapter 4). Finally, I examined whether short-term type-related dynamics may shape long-term changes by studying how hourly coupling between loneliness and depressive symptoms is related to their half-yearly changes in adolescents.

In the rest of this chapter, I introduce the theoretical underpinning on the four indices of type-related dynamics of emotions and their regulation: emotion regulation variability (Chapter 2), emotion differentiation (Chapter 3), emotion transition (Chapter 4), and temporal coupling between feeling lonely and feeling depressed (Chapter 5). I elaborate on the relevance of these type-related dynamics to the daily lives of young people and state the related research questions. Before Chapter 1 ends, I introduce the study designs and datasets I used to answer these research questions.

1.2 Type-Related Dynamics in Emotion and Emotion Regulation: Theoretical Underpinning and Research Questions

This subsection begins with the question that originally motivated this dissertation: does knowing what one feels change how they regulate their emotions (Chapter 3)? However, addressing this question first required resolving a methodological issue in capturing changes in emotion regulation (Chapter 2). Accordingly, this subsection follows the order in which the questions were posed. In contrast, the main chapters follow the sequence in which I arrived at the answers, with Chapter 2 laying the methodological groundwork that precedes the analyses presented in Chapter 3.

1.2.1 Knowing what one feels before regulating one's emotions (Chapter 3)

Emotion differentiation is theorized to help one regulate one's emotions (Barrett et al., 2001; Berking & Whitley, 2014; Erbas et al., 2014; Kashdan et al., 2015). Put simply, emotion differentiation is about knowing what one feels. It is defined as distinctively labeling the emotions and describing how intense each emotion is (Barrett et al., 2001; Erbas et al., 2014). With high emotion differentiation, individuals have clarity in their emotional experience. Consequently, with clarity, individuals can comprehensively evaluate of the context they are in (Schwarz & Clore, 1983) and, in the case of negative emotions, what they need for themselves (Greenberg, 2006). With poor emotion differentiation, individuals have muddled emotional experience. Consequently, they have an unclear action tendency in regulating their emotions. Against this background, that it was theorized that emotion differentiation should facilitate emotion regulation (Kashdan et al., 2015). Empirically, individuals with good emotion differentiation tend to have enhanced functioning and good mental health (see review by Ozomaro et al., 2025). Building on these theoretical and empirical work, there is increasing interest to develop self-guided and online interventions that target emotion differentiation for improving emotion regulation (Matt et al., 2024; Seah & Coifman, 2024; Van der Gucht et al., 2019). However, findings based on individual differences do not necessarily generalize to within-person relations (Curran & Bauer, 2011; Molenaar, 2004). Before targeting emotion differentiation in interventions, it is therefore important to clarify the theorized effects of emotion differentiation on emotion regulation.

Emotion differentiation's effect on emotion regulation might be particularly pronounced in young people. In the middle of adolescence, they experience a temporary dip in emotion differentiation as their emotional experience becomes more complex (i.e., more frequently experiencing multiple emotions) (Nook et al., 2018). Some experimental studies even suggest that putting emotional experience into words can be counterproductive for regulating their emotions (Nook, Satpute, et al., 2021). However, in young people's daily lives, where they must respond to contextual demands that are far more diverse and complex than experimental setups, it is unknown whether emotion differentiation is facilitating emotion regulation, as theorized, or hinders it, as shown in previous experimental studies.

To examine the theorized link between emotion differentiation and emotion regulation, it is important to consider regulation in two aspects: (1) the strategies adolescents use to influence their emotions (Kalokerinos et al., 2019; Sels et al., 2024), and (2) the resulting emotion intensity, reflecting the outcome of those strategies (Webb et al., 2012). In other words, if emotion differentiation indeed affects emotion regulation, fluctuations in emotion differentiation within young people should shape their selection of regulation strategies, which in turn influence emotion intensity. Therefore, Chapter 3 investigates this question: Do young people's levels of emotion differentiation affect how they deploy emotion regulation strategies and how they feel afterward?

1.2.2 Examining Variability in Multiple Emotion Regulation Strategies (Chapter 2)

Emotion regulation in young people is crucial for them to navigate adolescence and young adulthood with emotional challenges and development opportunities (Bailen et al., 2019; Grosse & Streubel, 2024; Nook et al., 2018, 2020; Reitsema et al., 2022; Sisk & Gee, 2022; Zimmermann & Iwanski, 2014). Adaptive regulation of negative emotions in daily life is particularly important as it shapes their long-term social and mental health (Aldao et al., 2016; McLaughlin et al., 2011; Preece et al., 2021; Silvers, 2022). Traditionally, emotion regulation researchers have been interested in understanding which strategy works (best) in reducing negative emotion intensity (Aldao et al., 2010; Webb et al., 2012). For example, among strategies shown in Table 1.1, reappraisal (i.e., thinking of silver linings) and problem solving (i.e., taking action to change the situation) are considered to be generally adaptive strategies.

Table 1.1
Strategies of Negative Emotion Regulation as Covered in the Datasets Analyzed in This Dissertation

Strategy (Reference)	What the strategy does
Expression (Chervonsky & Hunt, 2017)	The external display and communication of one's emotional state or behavioral intentions.
Suppression (Chervonsky & Hunt, 2017)	The active inhibition of the expressive components of emotion.
Acceptance (Rompilla et al., 2022)	Embracing negative emotional experience
Self-Compassion (Berking & Whitley, 2014; Gilbert, 2014)	Directing empathy towards oneself and a desire to help oneself in difficult situations
Distraction (Wolgast & Lundh, 2017)	Redirecting attention towards something else
Reflection (Brans et al., 2013; Trapnell & Campbell, 1999)	Self-reflection in a positive manner, driven by curiosity
Worry (Borkovec et al., 2004)	Worrying about future negative events repetitively
Rumination (Joormann et al., 2006; Nolen-Hoeksema et al., 2008)	Thinking repetitively about past negative events and their causes and consequences
Reappraisal (Ford & Troy, 2019)	Reframing about the situation that elicit emotions in a benign or positive way
Avoidance (Aldao et al., 2010)	Ignoring or avoiding the emotions or situations that elicited them
Problem Solving (Aldao et al., 2010)	Attempting to change the situation that elicited the emotions
Social Sharing (Rimé et al., 1992)	Sharing one's emotions with others
Co-Brooding (Horn & Maercker, 2016; Rose, 2002)	Co-ruminating with others

However, beyond these general tendencies, the contexts in which strategies are deployed matter. Strategies are not universally adaptive (Bonanno & Burton, 2013). For instance, even though reappraisal has been considered as generally adaptive, individuals who have high levels of depressive symptoms are found to habitually apply reappraisal - just that they reappraises controllable situations, where they could have instead taken action to change undesirable situations (Troy et al., 2013). Flexibly using the right strategies at the right time in a matching context may be more adaptive than applying a single "generally adaptive" strategy everywhere (Aldao et al., 2015; Birk & Bonanno, 2016).

This strategy-context fit is built on the foundation of emotion regulation variability. Without variability, it is impossible for young people to use emotion regulation strategies to influence their emotions as contextual demands change. Borrowing Aldao et al. (2015)'s analogy, without variability, it is like a streetlamp that is always turned off, which cannot possibly adapt to changing daylight conditions. With variability in deploying emotion regulation strategies (as the foundation of adaptive flexibility), individuals are expected to be more likely to reach low negative emotion intensity than when they are not (Bonanno

& Burton, 2013). Relevant to this the earlier emotion differentiation-regulation research question (Section 1.2.1), emotion regulation variability was the outcome variable in Chapter 3.

Emotion regulation variability is theorized to involve two processes: endorsement change, referring to overall initiation or inhibition of emotion regulation, and strategy switching, referring to switching from using one type of strategy to another (Aldao et al., 2015). Although emotion regulation researchers have been keen to study emotion regulation variability, this variability has only been studied restrictively. In a few laboratory studies, strategy switching was studied, but only with limited breadth because switching was restricted to only between two strategies (Adamczyk et al., 2024; M. S. Chen et al., 2024). In studies about individuals' daily lives, it is common for researchers to measure multiple emotion regulation strategies (e.g., Blanke et al., 2020; X. Wang et al., 2021). However, emotion regulation variability is either studied within a strategy across time (within-strategy variability, e.g., how much one fluctuates in thinking of silver linings across time) or between strategies at one moment (between-strategy variability, e.g., does one focus on using one strategy or multiple different strategies at a given time), but not altogether between strategies and across time. These conventional approaches could not sufficiently detect strategy switching. Up till now, little is known about whether strategy switching affects subsequent negative emotion intensity in daily life.

A likely reason for this gap is methodological. Research on emotion regulation variability has largely relied on standard deviation, which supports the analysis of within-strategy and between-strategy variability separately (Blanke et al., 2020; X. Wang et al., 2021). However, there has been a lack of tools to capture variability across multiple strategies and time points simultaneously. In search of a suitable methodology for Chapter 3, I was delighted to find that we might not need to reinvent the wheel. Promising methods already exist in other fields. In ecology, researchers have been using Bray-Curtis dissimilarity to study type variability for decades, such as when one species replaces another over time (Bray & Curtis, 1957; Pyron et al., 2006). Yet, the reliability of Bray-Curtis dissimilarity has not been tested when applied to psychological data, particularly emotion regulation data.

To address the methodological gap and clarify the theorized role of emotion regulation variability in enabling adaptive flexibility in regulating negative emotions, Chapter 2 addresses two questions. First, methodologically, is Bray-Curtis dissimilarity a suitable approach to measure emotion regulation variability that takes into account both endorsement change and strategy switching? Second, related to the overarching aim of this dissertation, to what extent are these two processes related to subsequent negative emotion intensity in the short term?

1.2.3 Variability in Negative Emotions: Not Just in Intensity but Between Types (Chapter 4)

Just as everyday emotion regulation is better understood dynamically in terms of its variability, so too are emotions. A useful framework for examining emotion variability is the dynamic systems perspective. Under this perspective, emotions form a system because emotions are interconnected and predict each other over time (Hollenstein, 2015; Thelen et al., 1991). The emotion system is treated as a unit of analysis. Within this multiple emotion system, variability is not noise (e.g., measurement error) but a meaningful signal about the state and functioning of the system (Van Geert & Van Dijk, 2002). Practically, emotion variability enables the system to respond to internal cues, such as physiological arousal and cognitive appraisal, as well as external perturbations, such as changing contexts. This is just like how an ecosystem needs variability to adjust to internal (for example, population changes) and external (for example, weather shifts) forces (Hollenstein, 2015; M. D. Lewis, 2005). If emotions do not exhibit variability, the emotion system cannot be adaptive and can be described as inflexible.

Apart from variability in intensity (i.e., negative emotions getting stronger or weaker), variability in the type of emotions (e.g., a transition from anger to fear) is also a form of variability which the dynamic systems framework expects to enable adaptiveness in manners that Hollenstein et al. (2013) named as *reactive* or *dynamic*. An emotion system transitions between emotions *reactively* across contexts so that it can adapt to external changes. An emotion system transitions between emotions *dynamically* within the same context so that it can (a) make micro-adjustments to maintain engagement with the context or (b) access different action tendencies (e.g., anger for defending one's rights, fear for avoiding threats) in preparation to change the context. Indeed, there is empirical support that more emotion transitions are associated with less internalizing symptoms in children and lower levels of depressive symptoms in adolescents (Van der Giessen et al., 2015). Aligned with the dynamic systems perspective, theoretical and empirical work in psychotherapy suggested that transitions between negative emotions can be therapeutically productive in leading to short-term reduction in negative emotion intensity (Singh et al., 2021).

Young adulthood is a developmental period marked by intensified negative emotions and a greater capacity to distinguish emotional experiences. Altogether, these developmental changes make transitions between negative emotions more likely compared to early adolescence. Low variability in negative emotion intensity during this period has been associated with poor mental health outcomes (Jahng et al., 2008; Koval, Pe, et al., 2013). Therefore, clarifying whether negative emotion transitions co-occur with changes in the overall intensity in young adults' daily lives is particularly important. However, it remains unclear whether the short-term intensity-reducing effects of transitions between negative emotions generalize beyond the therapy setting to daily life in community samples of young adults.

This transition–intensity reduction effect, if present in daily life, may not be uniform across individuals. It may depend on individual differences in depressive symptomatology, which is closely linked with emotional inflexibility (Garvey et al., 1989; Holtzheimer & Mayberg, 2011; Kashdan & Rottenberg, 2010; Wen & Yoon, 2019). Becoming emotionally flexible, even temporarily, appears to provide relief for individuals with depressive symptoms. Compared to healthy individuals, depressed individuals had greater decrease in negative emotion when they encountered everyday positive events (Bylsma et al., 2011; Khazanov et al., 2019; Panaite et al., 2019; van Loo et al., 2023). However, it remains unknown whether the transition-intensity reduction effect, if present in daily life, is stronger in those with higher levels of depressive symptoms. To address these gaps, Chapter 4 investigates (a) whether transitions between negative emotions in daily life are associated with short-term reductions in negative emotion intensity, and (b) whether the transition-intensity reduction association in negative emotions is stronger for young adults reporting higher levels of depressive symptoms.

1.2.4 How Short-Term Coupling Between Loneliness and Depressive Symptoms Shapes Their Long-Term Changes (Chapter 5)

The dynamic systems perspective, which has theoretically informed the previous research questions, also emphasizes that dynamics of emotion systems are interconnected across timescales. Specifically, short-term dynamics of emotion systems may accumulate to shape long-term outcomes in the sensitive developmental period of adolescence (Granic, 2005; Jordan, 2013). Aligned with this view, the Evolutionary Theory of Loneliness (ETL) proposes that moment-to-moment interactions between loneliness and depressed feelings may gradually shape enduring changes in both loneliness and depressive symptoms over time (Cacioppo & Cacioppo, 2018). Understanding loneliness and depressive symptoms is especially relevant for adolescents, as loneliness and depressive symptoms are quite prevalent among adolescents and often co-occur.

The ETL proposes that transient loneliness can trigger short-term depressed feelings, which serve two adaptive functions. First, depressed feelings promote social withdrawal, helping adolescents avoid additional socially painful experiences that might result from initiating new interactions. Second, depressed feelings may serve a communicative function: when expressed, depressed feelings can signal needs for care and elicit support from trusted others (Allen & Badcock, 2003; Balsters et al., 2013; Qualter et al., 2015). In this way, depressed feelings triggered by loneliness may act as a bridge between the internal signal of loneliness and fulfillment of the underlying need for social connection, which in turn helps to reduce loneliness. In summary, the emotions of feeling lonely and feeling depressed form a short-term balancing feedback loop. If this adaptive short-term feedback loop fails, loneliness and depressed feelings may become long-term trait loneliness and depressive symptoms that exacerbate each other over time. In summary, loneliness and depressive symptoms form a long-term reinforcing feedback loop.

Current evidence supporting the feedback loops proposed by the ETL requires careful re-examination. Regarding the short-term balancing loop, prior studies have primarily tested the temporal link from loneliness to depressed feelings, while the reverse link, depressed feelings preceding loneliness, remains largely unexamined (Kuczynski et al., 2024; Speyer et al., 2024; Yung et al., 2023). Regarding the long-term reinforcing loop, many findings rely on traditional cross-lagged panel models (Danneel et al., 2019; Lapierre et al., 2019; Lasgaard et al., 2011; Vanhalst et al., 2012). These models have come under criticism in recent years for conflating within-person dynamics with stable between-person differences, which can bias estimates in within-person changes (Hamaker, 2023; Kristensen et al., 2023; Lucas, 2023). Furthermore, the ETL's hypothesis that short-term mutual influences between loneliness and depressive symptoms shape their long-term changes has not yet been formally tested in adolescents. To address these gaps, Chapter 5 set out to answer: (a) In adolescents' daily lives, do loneliness and depressed feelings happen one after another in the short term, (b) do such balancing short-term relations buffer against the long-term increases in loneliness and depressive symptoms, and (c) do loneliness and depressive symptoms exacerbate each other over the long term?

1.3 Overview of Studies and Datasets Used

To address the research questions of this dissertation, seven existing datasets were analyzed. Six of the seven datasets were experience sampling methods (ESM) datasets. ESM is a structured diary method in which participants report their emotions and use of emotion regulation strategies several times in their daily lives (Myin-Germeys et al., 2009). ESM provides temporally fine-grained, ecologically valid data (Trull & Ebner-Priemer, 2020) that allow me to investigate short-term emotion (regulation) dynamics in young people's daily lives. The seventh dataset, a longitudinal study, together with one of the ESM datasets, belongs to the same project, G(F)ood together (van den Broek et al., 2023). Detailed descriptions of study designs, recruitment procedures, and participant characteristics are provided in the corresponding chapters and their supplementary materials. In Table 1.2, I present an overview of these datasets.

Table 1.2
Overview of Studies and Datasets Used

Project (Reference)	Institute	N (% Female)	Age: M (SD), range	Sampling Interval	ESM observations per day (number of days)	Total Number of Observations Across Participants	Measures	Used in Chapter
G(F)ood together (Longitudinal study) (van den Broek et al., 2023)	Radboud University, the Netherlands	777 (53%)	12.9 (0.7), 11.5-14.5 (at first assessment)	6 to 18 months	Not applicable	1880	**Depressive Symptoms**: Center for Epidemiological Studies Depression scale, 10-item short form **Loneliness**: Louvain Loneliness Scale for Children and Adolescents: Friend scale (12 items)	5
G(F)ood together (ESM study) (Verhagen et al., 2022)	Radboud University, the Netherlands	83 (57%)	16.4 (0.7), 15.0-18.0	1.5 hours	10 (7 days)	3550	**Positive Emotions** (4 items): Content, Relaxed, Joyful, Energetic Negative Emotions (5 items): Irritated, Worried, Depressed, Insecure, Lonely Emotion Regulation Strategies (5 items): Rumination, Reappraisal, Suppression, Acceptance, Social Sharing	3, 5
Mindfulness in Daily Life (Riediger et al., 2009)	Humboldt-Universität zu Berlin, Germany	70 (50%)	25.6 (2.7), 20.0-30.0	1.5 hours	10 (7 days)	3426	**Negative Emotions** (3 items): Nervous, Downhearted, Distressed **Emotion Regulation Strategies** (6 items): Rumination (thoughts), Rumination (feelings), Distraction (thoughts), Distraction (feelings), Reflection (thoughts), Reflection (feelings)	2, 4
Emotions in Daily Life (Koval, Ogrinz, et al., 2013)	KU Leuven, Belgium	97 (63%)	19.1 (1.3), 18.0-24.0	1.5 hours	10 (7 days)	5816	**Positive Emotions** (2 items): Relaxed, Happy **Negative Emotions** (4 items): Angry, Anxious, Depressed, Sad **Emotion Regulation Strategies** (6 items): Rumination, Reappraisal, Distraction, Reflection, Suppression, Social Sharing	2, 3, 4

Table 1.2

Overview of Studies and Datasets Used (continued)

Project (Reference)	Institute	N (% Female)	Age: M (SD), range	Sampling Interval	ESM observations per day (number of days)	Total Number of Observations Across Participants	Measures	Used in Chapter
3-wave Longitudinal Study (Erbas et al., 2018)	KU Leuven, Belgium	202 (55%)	18.3 (1.0), 17.0-24.0	1.5 hours	10 (7 days)	12346	**Positive Emotions** (3 items): Happy, Relaxed, Cheerful **Negative Emotions** (6 items): Angry, Anxious, Depressed, Sad, Lonely, Stress **Emotion Regulation Strategies** (6 items): Rumination, Reappraisal, Distraction, Worry, Suppression, Social sharing	2, 3, 4
Emotions in Daily Life (Van Roekel & Trompetter, 2023)	Tilburg University, the Netherlands	178 (78%)	20.9 (0.7), 18.0-25.0	3 hours	5 (14 days)	7904	**Positive Emotions** (7 items): Enthusiastic, Content, Energetic, Calm, Determined, Cheerful, Grateful **Negative Emotions** (6 items): Angry, Irritated, Depressed, Sad, Nervous, Bored **Emotion Regulation Strategies** (7 items): Rumination, Distraction, Avoidance, Problem Solving, Acceptance, Co-brooding, Social Sharing	3
Outside-in (Braet et al., 2025)	Ghent University, Belgium	218 (48%)	13.5 (0.6), 11.0-15.0	3 hours	5 (14 days)	9836	**Positive Emotions** (3 items): Happy, Calm, Enthusiastic **Negative Emotions** (6 items): Angry, Insecure, Afraid, Sad, Stressed, Bored **Emotion Regulation Strategies** (8 items): Rumination, Reappraisal, Distraction, Self-Compassion (Support), Self-Compassion (Cheer-up), Expression, Suppression, Social Sharing	3

1.4 The Present Dissertation

In this dissertation, I examine type-related dynamics of emotion and emotion regulation in adolescents and young adults' daily lives. The overarching aim of this dissertation is to study whether and how type-related emotion (regulation) dynamics are related to short-term emotion outcomes and long-term social and mental health.

Chapter 2 addresses both a methodological and a substantive research question. First, it examines whether **Bray-Curtis dissimilarity** is suitable for capturing **emotion regulation variability**, with sensitivity to both changes in overall strategy endorsement and the switching between strategies. Second, it investigates whether these two components of emotion regulation variability (endorsement change and strategy switching) are associated with subsequent negative emotion intensity in young adults.

Chapter 3 focuses on the role of **emotion differentiation** in shaping regulation and emotional experience. Specifically, it investigates whether adolescents' and young adults' differentiation of their emotions changes how they deploy emotion regulation strategies and how they subsequently feel.

Chapter 4 explores whether **transitions between negative emotions** in young adults' daily lives are associated with short-term reductions in negative emotion intensity. Extending this inquiry, the chapter also examines whether this hypothesized transition–intensity reduction association varies by young people's depressive symptoms.

Chapter 5 shifts focus to the temporal dynamics between social and emotional experiences. It investigates whether and how adolescents' **loneliness and depressive symptoms** occur in hourly succession and are related across a half-yearly timescale. Furthermore, the chapter examines whether hourly coupling between loneliness and depressive symptoms predicts their long-term changes, linking short-term emotion dynamics to long-term social and mental health outcomes.

Chapter 6 provides a comprehensive synthesis of the dissertation. It begins with a summary of key findings across the empirical chapters, followed by reflections from theoretical, developmental, and methodological perspectives. This chapter offers suggestions for how future research can address limitations of this dissertation and expand on the current work. It also outlines practical implications for young people and clinicians, before arriving at the conclusion of this dissertation.

2

A Theory-Informed Emotion Regulation Variability Index: Bray–Curtis Dissimilarity

This chapter is based on:
Lo, T. T., Van Lissa, C. J., Verhagen, M., Hoemann, K., Erbaş, Y., & Maciejewski, D. F. (2024). A theory-informed emotion regulation variability index: Bray–Curtis dissimilarity. *Emotion*, *24*(5), 1273. https://doi.org/10.1037/emo0001344

ABSTRACT

Emotion regulation (ER) variability refers to how individuals vary their use of ER strategies across time. It helps individuals to meet contextual needs, underscoring its importance in well-being. The theoretical foundation of ER variability recognizes two constituent processes: strategy switching (e.g., moving from distraction to social sharing) and endorsement change (e.g., decreasing the intensity of both distraction and social sharing). ER variability is commonly operationalized as the standard deviation (*SD*) between strategies per observation (between-strategy *SD*) or within a strategy across time (within-strategy *SD*). In this paper, we show that these *SD*-based approaches cannot sufficiently capture strategy switching and endorsement change, leading to ER variability indices with poor validity. We propose Bray-Curtis dissimilarity, a measure used in ecology to quantify biodiversity variability, as a theory-informed ER variability index. First, we demonstrate how Bray-Curtis dissimilarity is more sensitive than *SD*-based approaches in detecting ER variability through two simulation studies. Second, assuming that higher ER variability is adaptive in daily life, we test the relation between ER variability and negative affect (NA) in three experience sampling method (ESM) datasets (total N = [70, 95, 200], number of moment-level observations = [5040, 6329, 14098]) At both the moment-level and person-level, higher Bray-Curtis dissimilarity predicted lower NA more consistently than *SD*-based indices. We conclude that Bray-Curtis dissimilarity may better capture moment-level within-person ER variability and could have implications for studying variability in other multivariate dynamic processes. The paper is accompanied by an R tutorial and practical recommendations for using Bray-Curtis dissimilarity with ESM data.

Keywords: Emotion Regulation, Variability, Dynamics, Within-Person, Experience Sampling Methods

A THEORY-INFORMED EMOTION REGULATION VARIABILITY INDEX: BRAY-CURTIS DISSIMILARITY

Emotion regulation (ER) is the process of increasing, maintaining, or reducing the intensity of emotions (Gross, 2015). People may employ different ER strategies to influence the level of their emotions. For instance, upon hearing about the war outbreak in East Ukraine, people may regulate their anxiety about their safety by redirecting attention (e.g., listening to music on radio; distraction), seeking validation and comfort from others (e.g., sharing feelings with friends; social sharing), or considering different perspectives on the situation (e.g., considering how the conflict may call for more international attention; reappraisal). From moment to moment, individuals may change their ER strategies in response to changes in their emotion intensity (Ford et al., 2017) and changes in the situational context (Sheppes et al., 2014).

This change in ER strategies within individuals across time has been coined *ER variability* (Aldao et al., 2015). ER variability is low when individuals tend to maintain the same strategies to the same extent – for example, distracting themselves by listening to the radio for hours. ER variability is high when individuals change the extent to which they use ER strategies or switch between different ER strategies – for example, when one pauses from using the radio as distraction, or switches from distraction to social sharing. ER variability is needed to flexibly adapt to changing contexts and is fundamental to mental health (Kashdan & Rottenberg, 2010).

To assess ER variability, researchers commonly use experience sampling methods (ESM), where individuals repeatedly report on their ER strategies over time and across situations. At each prompt, participants are asked to rate the intensity of the extent they have used different ER strategies. Using these data, researchers often operationalize ER variability using the standard deviation (*SD*) of intensity ratings, either across strategies or across time (Aldao et al., 2015; Blanke et al., 2020). However, as we will argue in the following sections, this operationalization does not fully capture ER variability and may therefore have poor construct validity. Drawing on inspirations from ecology, we propose Bray-Curtis dissimilarity – a measure to quantify biodiversity variability – as a theory-informed ER variability index. In this paper, we review how Bray-Curtis dissimilarity matches the theoretical foundations of ER variability and evaluate its performance in two simulations and one empirical study.

The Theoretical Foundation of ER Variability

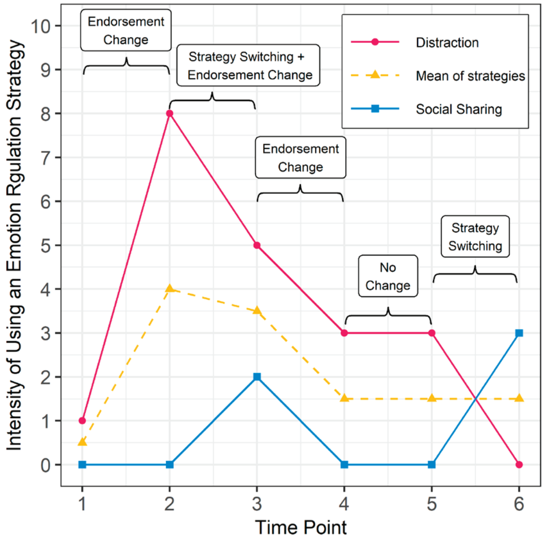
ER variability is defined as the variation in the use of one or more ER strategies across time (Aldao et al., 2015). It is one way of studying ER from a dynamic process perspective. Compared to a static view of ER, which focuses on how ER strategies are implemented on average, a dynamic approach is interested in the ebbs and flows of how people flexibly implement strategies to meet their goals and situational demands. Most dynamic measures are person level, which means they describe an individual's dynamics over the period of study (e.g., one week or one month). For example, ER inertia, calculated as autocorrelation, refers to the degree of how much a particular strategy is carried over from one time point to the next (for other person-level indices, such as pulse, spin, and instability, see Timmermans et al., 2010; and Wenzel et al., 2021). Person-level summaries of dynamics, while informative for studying interindividual differences, do not give a moment-to-moment analysis on how dynamics change within individuals, which is useful for studying how these momentary dynamics predict subsequent levels of other variables (see Erbas et al., 2021). For instance, research suggests that momentary ER variability is related to moment-to-moment changes in negative emotions (Blanke et al., 2020). Additionally, in a renewed ER framework that adopts the dynamic perspective, moment-level ER variability is an intermediate step to further calculate how ER strategies are flexibly applied to changing contexts (Aldao et al., 2015).

To illustrate the concept of ER variability, let us imagine a person, Edmund, who casually listens to the radio for distraction from boredom. He becomes anxious upon hearing news of the war outbreak in East Ukraine. As a response to his anxiety, Edmund increases the intensity of distraction by tuning in to a music channel on the radio. Over time, he decreases the intensity of distraction and briefly increases in social sharing by calling a friend who agrees to meet later in the day, after which he continues to listen to the radio. In the following hours, Edmund continues to use distraction until he meets his friend and shifts to primarily using social sharing (Figure 2.1).

ER variability can be divided into within-strategy variability and between-strategy variability (Aldao et al., 2015). *Within-strategy variability* concerns variability in a person's use of a particular ER strategy over time, whereas *between-strategy variability* refers to differences in a person's use of multiple ER strategies at a particular moment. In our example, within-strategy variability could refer to changes in how much Edmund listens to the radio (i.e., uses distraction) over the course of the day, whereas between-strategy variability could be how much Edmund differs in his use of distraction versus social sharing at a given time point. To fully capture the complexity of ER dynamics across time, within-strategy and between-strategy variability should be jointly examined (Aldao et al., 2015). For instance, when Edmund decreases his use of distraction, it is necessary to know whether this is accompanied by increased social sharing: if yes, Edmund continues regulating but switches strategies (e.g., Time 5 to Time 6 in Figure 2.1); if no, Edmund reduces his overall intensity of ER (e.g., Time 3 to Time 4 in Figure 2.1). This example points out two important processes that are central in our understanding of ER variability, namely *strategy switching* and *endorsement change*.

Figure 2.1

Edmund's Use of Two Emotion Regulation Strategies across Six Time Points



Note. This figure depicts examples of no change in emotion regulation strategy use, strategy switching, and endorsement change. Values of this example can be found in Table 2.1.

Strategy switching is marked by reprioritizing and redeploying ER strategies across time, which might be related to optimal use of cognitive resources (Grillon et al., 2015) or flexible adaptation to changing situations (Sheppes et al., 2014). In Edmund's example, he switches from listening to the radio (i.e., distraction) to seeking support from friends (i.e., social sharing) from Time 5 to Time 6 (Figure 2.1). Strategy switching can be identified by antagonistic changes in strategy ratings from one moment to the next (i.e., social sharing going up from an intensity of 0 to an intensity of 3, and distraction going down from an intensity of 3 to an intensity of 0). *Endorsement change* is marked by moment-to-moment increases or decreases in the ratings of the same strategy or strategies, which may indicate initiation and inhibition of ER (Aldao et al. 2015). In Edmund's example, an endorsement change happens when he decreases both distraction and social sharing after he finishes a phone call with his friend from Time 3 to Time 4. Endorsement change can be identified by changes in mean strategy ratings (i.e., mean changed from 3.5 to 1.5; Figure 2.1). Importantly, strategy switching and endorsement change can happen together, such as when Edmund briefly calls his friend at Time 3. From Time 2 to Time 3, the rating of distraction decreases from 8 to 5, and the rating of social sharing increases from 0 to 2. In this example, there are both antagonistic changes (i.e., increasing social sharing while decreasing distraction) and a change of overall mean ratings (from 4.0 to 3.5), indicating simultaneous strategy switching and endorsement change.

To summarize, ER variability comprises both within-strategy and between-strategy variability, which need to be jointly examined to fully characterize ER processes. With this in mind, a valid index of ER variability should be sensitive to both changes in the composition of strategies at a given moment (i.e., strategy switching) as well as the changes in the extent of employing strategies over time (i.e., endorsement change).

The Need to Move beyond the *SD*

Researchers who investigate ER variability based on Aldao et al. (2015)'s framework have commonly examined ER variability by separately calculating within-strategy and between-strategy variability with the standard deviation (*SD*), which reflects how scores deviate from their mean. Within-strategy variability is operationalized as the *SD* of multiple scores across time within one strategy (within-strategy *SD*); between-strategy variability is the *SD* across multiple strategies within one time point (between-strategy *SD*). For instance, following this approach, Blanke et al. (2020) showed that higher within-strategy *SD* was associated with higher negative affect (NA) at the person-level (i.e., across individuals), whereas higher between-strategy *SD* was associated with lower NA at both the moment-level (i.e., across observations within a person) and the person-level.

However, operationalizing ER variability as the *SD* has potentially poor construct validity for several reasons. First, the *SD* approach only evaluates ER scores across time (within-strategy variability) or across strategies (between-strategy variability), but not across both, making it impossible to capture the full complexity of ER variability in one index. Second, the *SD* is agnostic to the positions of data. That is, the within-strategy *SD* will be the same for the same ER scores no matter how they were temporally ordered, and the between-strategy *SD* will be the same no matter which strategies were used so long as the distribution of endorsement across strategies remains the same. As such, no information about the patterns of variation across time and between strategies can be retrieved from the *SD*. Even if we look beyond the between-strategy *SD* at a specific moment by considering the temporal changes of between-strategy *SD* across time (as suggested in Aldao et al., 2015), endorsement change and strategy switching may remain undetected. This is demonstrated from Time 3 to 6 in Table 2.1, where the between-strategy *SD* remains 2.12 at all time-points, even though Edmund first decreases use of both strategies (endorsement change) and later switches completely from distraction to social sharing (strategy switching). In view of these limitations, *SD*-based indices of ER variability may not reflect what the theoretical framework of ER variability posits that it should capture.

Table 2.1

Different ER Variability Indices Calculated from Artificial Data of Edmund

Time point	Distraction	Social sharing	Moment-level mean	Between-strategy SD	Bray-Curtis dissimilarity	Replacement subcomponent	Nestedness subcomponent
1	1	0	0.50	0.71	-	-	-
2	8	0	4.00	5.66	0.78	0.00	0.78
3	5	2	3.50	2.12	0.33	0.29	0.05
4	3	0	1.50	2.12	0.40	0.00	0.40
5	3	0	1.50	2.12	0.00	0.00	0.00
6	0	3	1.50	2.12	1.00	1.00	0.00
Strategy mean	3.33	0.83					
Within-strategy *SD*	2.88	1.33					

Note. Two ER strategies rated on a scale of 0 to 10 over six time points. No Bray-Curtis dissimilarity or its subcomponents were calculated for time point 1 because there is no previous time point.

Inspirations from Ecology: Bray-Curtis Dissimilarity

One promising candidate for studying ER variability in its full complexity is Bray-Curtis dissimilarity. As given by Equation 1, Bray-Curtis dissimilarity is calculated as the sum of absolute differences within the same element (x_i) across two observations (j and k), divided by the sum of all elements across observations:

$$\text{Bray-Curtis dissimilarity} = \sum_{i=1}^{N} \frac{|x_{ij}-x_{ik}|}{x_{ij}+x_{ik}} \quad (1)$$

Ecologists have used this measure to solve similar research questions, namely quantifying biodiversity variability in observations made across time or space. For example, Bray-Curtis dissimilarity has been used to calculate the temporal variability of species of fish across 25 years (Pyron et al., 2006). Bray-Curtis dissimilarity ranges from 0 to 1; near-zero values indicate that observations are highly similar across time points and across species. Increasing values represent increasingly different observations across time (e.g., a year with many fishes dying gives higher Bray-Curtis dissimilarity compared to other yearly fluctuations).

Ecologists often partition the Bray-Curtis dissimilarity index into two subcomponents, replacement and nestedness, to investigate potentially distinct processes that drive biodiversity variability (Baselga, 2013b)[1]. *Replacement* in species refers to decreases in numbers in some species and increases in some others. This pattern of change may reflect the

1 Replacement and nestedness add up to the full Bray-Curtis dissimilarity index. Formulae for calculating the two subcomponents are provided in Supplemental Material 1.

temporal processes in competition between species for finite resources, or their different adaptability to changing habitat conditions. Replacement, marked by antagonistic changes in numbers in different species, is numerically analogous to strategy switching in ER variability. *Nestedness* in species refers to a uniform shrinkage or growth of numbers in all species. This pattern of change may reflect changes in the habitat that affect general survivability, such as pollution or temperature change. Nestedness, marked by increases or decreases of mean number of all species, is numerically analogous to endorsement change in ER variability.

If we treat ratings of ER strategies from ESM data as the number of species in ecological data over time, there are clear similarities in calculating ER variability and biodiversity variability. Therefore, we expect similar advantages in partitioning Bray-Curtis dissimilarity to capture different sources of ER variability in ESM data. To illustrate, we calculated Bray-Curtis dissimilarity for Edmund's day in Table 2.1 with equation (1) by comparing the moment of interest (*t*) with the previous moment (*t*-1). This approach to comparison is referred to as the successive difference (e.g., Burr et al., 2021) and emphasizes the temporal order of the ER process (Kalokerinos et al., 2017). In Edmund's ESM data, the full Bray-Curtis dissimilarity index is given as the sum of absolute differences within each strategy across two moments, divided by the sum of all ratings. For instance, from Time 2 to Time 3, the absolute difference within distraction is $|8 - 5| = 3$, and the difference within social sharing is $|0 - 2| = 2$. The sum of all ratings is $(8 + 0 + 5 + 2 = 15)$. So, Bray-Curtis dissimilarity is given as $(3 + 2) / 15 = 0.33$. From Time 4 to Time 5, Bray-Curtis dissimilarity is 0 because the intensities of both ER strategies are the same. As can be seen in Table 2.1, the Bray-Curtis dissimilarity subcomponents on Edmund's data capture the two described ER processes. For example, the replacement subcomponent captured the endorsement change from Time 3 to Time 4, and the nestedness subcomponent captured the complete strategy switch from Time 5 to Time 6. These examples illustrate that Bray-Curtis dissimilarity is a promising index for capturing ER variability and its constituent processes.

The Present Studies

The aim of the present paper is to introduce Bray-Curtis dissimilarity as a theory-informed index that validly estimates ER variability. Based on the previous discussion, we expect Bray-Curtis dissimilarity to be more sensitive than current *SD*-based indices in detecting ER variability. We tested this hypothesis in two parts – two simulation studies and an empirical study. In the simulation studies, we manipulated simulation parameters to introduce the two constituent ER variability processes (i.e., endorsement change and strategy switching) and compared the performance of Bray-Curtis dissimilarity against *SD*-based indices (within-strategy *SD* and between-strategy *SD*)[2]. In the empirical study, assuming that higher ER variability is adaptive in daily life, we reanalyzed the data from Blanke et al. (2020) to compare the consistency and predictive power of Bray-Curtis dissimilarity against *SD*-based indices in predicting NA.

TRANSPARENCY, OPENNESS AND CODE AVAILABILITY

In respective sections under each study, we report how we determined sample sizes, manipulations, and measures and software used. This study's design and its analysis were not pre-registered. All data simulation and analyses in this paper were conducted in R (R Core Team, 2022). Following the Workflow for Open Reproducible Code in Science (Van Lissa et al., 2021), annotated code of all studies in this paper is publicly available at https://osf.io/vzh2n/. We also provide a tutorial on how to calculate Bray-Curtis dissimilarity and its two subcomponents with ESM data (https://github.com/taktsun/dissimilarity-for-ESM-data/).

PART I: SIMULATION STUDIES

We conducted two simulation studies to compare the sensitivity of different indices to the two constituent processes of ER variability, strategy switching and endorsement change. We made use of two different data generating mechanisms and manipulated a series of simulation parameters to influence the two processes in simulated datasets. In Simulation 1, we generated multivariate time series datasets with vector autoregressive (VAR) models, which are commonly used to model how emotion processes unfold over time (Adolf et al., 2021). VAR models describe how multiple variables predict one another at concurrent and following time points. A model with a lag of one time point is called a first-order VAR model, VAR(1). Manipulating VAR(1) parameters always influences the two ER variability processes simultaneously. One limitation of Simulation 1 is that it was not possible to test a scenario of primary strategy switching, or when ER variability is driven by strategy switching rather than endorsement change (e.g., when Edmund switched completely from distraction to social sharing between Time 5 and Time 6). A valid ER variability index should be sensitive to such a change in ER strategy composition across time.

Simulation 2 overcame this limitation by generating datasets with varying probability of strategy switching over time but without systematically introducing endorsement changes. We did this by resampling the Lorenz system (Strogatz, 2018). The Lorenz system is a

2 While Bray-Curtis dissimilarity has statistical properties that best match the theoretical foundation of ER variability, we also examined the sensitivity of another possible SD-based index pointed out by an anonymous reviewer and three other dissimilarity indices suitable for ER ESM data (Legendre & Legendre, 2012) to examine the robustness of our conclusions. None of them performed as well as Bray-Curtis dissimilarity. Related method and results are detailed in Supplemental Material 1 and 4.

well-studied symmetrical system that produces solutions of points in three-dimensional coordinates that look like a two-winged butterfly (under the classic system coefficients; see Supplemental Material 3). By treating the coordinates of the three axes as the levels of intensity of three ER strategies, the points on the two wings become possible intensity ratings of ER strategies where strategy switching could happen. In one of the wings, the ratings of strategy x are higher than those of strategy y (e.g., Edmund uses distraction but not social sharing at Time 5), whereas in the other wing, there are geometrically symmetrical ratings with ratings of strategy y being higher than those of strategy x (e.g., Edmund uses social sharing but not distraction at Time 6). As such, when we resampled points that rest on the two wings, a moment from one wing followed by a moment from the other wing resembles strategy switching. Due the symmetrical property of the Lorenz system, we can easily identify to which wing a point belongs, so that probability of strategy switching between wings can be manipulated. Importantly, the grand mean of coordinates in each of the two wings are the same, making it possible to manipulate strategy switching exclusively, without entailing a systematic change in overall mean between strategies (i.e., endorsement change).

Method

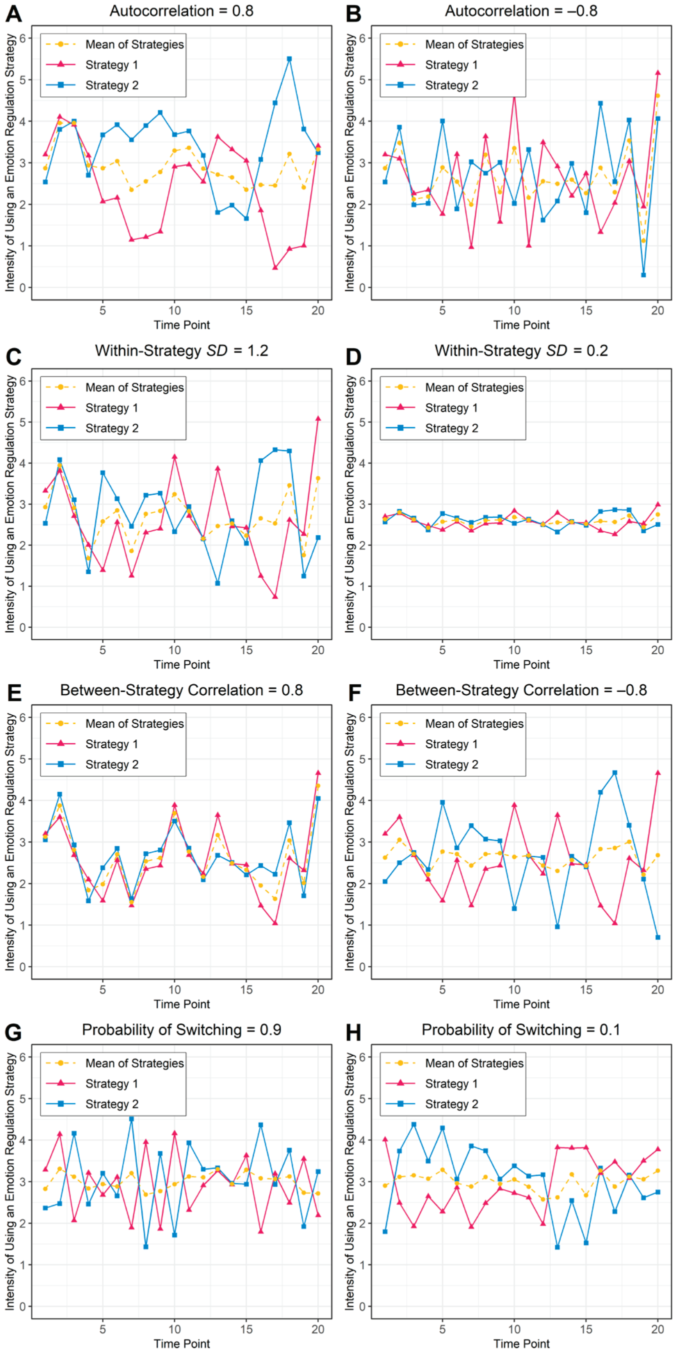
Simulation Parameters and Data Generation

Simulation 1: VAR(1) model. We set realistic values for five simulation parameters based on two ER experience sampling datasets (Blanke et al., 2020; van den Broek et al., 2023) [3]. In the following paragraphs, we first introduce the three parameters that are expected to influence the two constituent ER variability processes (i.e., strategy switching and endorsement change): within-strategy autocorrelation, within-strategy *SD*, and between-strategy correlation (see Figure 2.2 for simulated datasets). We did not specify a cross-correlation (i.e., correlation between one strategy at moment of interest *t* and another strategy at the previous moment *t*-1), as it is less empirically studied compared to the other included parameters.

3 Values of the autocorrelation, within-strategy *SD*, and between-strategy correlation parameters were chosen as one *SD* below the mean, the mean, and one *SD* above the mean of VAR(1) parameter estimates of the reference datasets (Blanke et al., 2020; van den Broek et al., 2023). Values of the number of ER strategies and the number of observations per participants parameters were chosen with reference to the same two reference datasets and study designs commonly seen in other ESM studies.

Figure 2.2

Influence of Four Simulation Parameters on ER Variability Processes



Note. Simulated datasets with two ER strategies in high and low values of four parameters (autocorrelation, within-strategy *SD*, between-strategy correlation, and probability of switching) in VAR(1) model (Panel A to F) and a resampled Lorenz system (Panel G to H).

A high autocorrelation means that each observation in the time series is similar to the previous observation (i.e., the rate of change is low). When the autocorrelation is high, the rate of antagonistic changes between ER strategies is relatively small, indicating low strategy switching (Figure 2.2A). Similarly, the change of mean ER strategy ratings across time is small, indicating low endorsement change (Figure 2.2A; smooth dotted line). The opposite is observed when the autocorrelation is low, where both strategy switching and endorsement change are relatively high (Figure 2.2B). Since the two processes are both negatively influenced by the autocorrelation, a valid ER variability index should also negatively associate with the autocorrelation parameter. In our simulation, we set the within-strategy autocorrelation parameter ∈ (-0.09, 0.12, 0.33)[4].

A high within-strategy *SD* means that there are relatively large fluctuations in the use of ER strategies over time (i.e., indicating a high amplitude of change). When the within-strategy *SD* is high, the amplitude of antagonistic changes between ER strategies is relatively large, indicating high strategy switching (Figure 2.2C). Similarly, the change of mean strategy ratings is relatively high, indicating high endorsement change (Figure 2.2C; spikey dotted line). The opposite is observed when the within-strategy *SD* is low, where both strategy switching and endorsement change are low (Figure 2.2D). Since the two processes are both positively influenced by the within-strategy *SD*, a valid ER variability index should also positively associate with the within-strategy *SD*. We set the within-strategy standard deviation parameter ∈ (0.10, 0.19, 0.28).

A high between-strategy correlation means that ER strategies tend to fluctuate in the same direction over time. Here, strategy switching and endorsement change are influenced in opposite directions. When the between-strategy correlation is high, there are relatively few antagonistic changes between ER strategies, indicating low strategy switching (Figure 2.2E; overlapping solid lines), but relatively high change of mean strategy ratings, indicating high endorsement change (Figure 2.2E; spikey dotted line). When the between-strategy correlation is low, there are relatively more strategy switches (Figure 2.2F; converging or diverging solid lines) but fewer endorsement changes (Figure 2.2F; smooth dotted line). If those two processes offset each other completely, a valid full ER variability index should associate weakly with the between-strategy correlation. We set the between-strategy correlation parameter ∈ (-0.11, 0.18, 0.47).

We specified two additional study design parameters: number of ER strategies ∈ (2, 3, 5, 6) and number of observations per participant ∈ (30, 70, 100). An ideal ER variability index should have wide applicability across different study designs and should be minimally affected by these parameters. We cross-tabulated the choices of values in five parameters to attain 324 unique profiles (an example profile is autocorrelation = 0.33, within-strategy

4 Numbers inside the ∈ () brackets are distinct choices of parameter values.

SD = 0.28, between-strategy correlation = 0.47, 6 ER strategies, and 100 observations). We replicated each unique profile 1,000 times to generate 324,000 multivariate time series datasets in VAR(1) model with the VAR.sim function in *tsDyn* package (Narzo et al., 2009), which by its default setting generates continuous data, and assumes multivariate normality and same mean ratings across all ER strategies and datasets. A full overview of the simulation setup can be found in Supplemental Material 2.

Simulation 2: Resampling the Lorenz System. We manipulated three simulation parameters. First, we set the probability of the switching parameter ∈ (.10, .30, .50, .70, .90) to simulate a wide range of frequencies of strategy switching. A high probability of switching means that the frequency of antagonistic changes between ER strategies is relatively high (Figure 2.2G), indicating high strategy switching. The opposite is seen when the probability of switching is low (Figure 2.2H), indicating low strategy switching. The mean of ER strategies randomly fluctuates regardless of the probability of switching (Figure 2.2G and 2.2H; dotted lines in similar smoothness), confirming that endorsement changes are not systematically affected by manipulating the probability of switching. As such, this simulation can better evaluate the performance of ER variability indices for primary strategy switching. Since strategy switching is positively influenced by the probability of switching, a valid ER variability index should positively associate with the probability of switching parameter.

Similar to Simulation 1, there were two study design parameters, number of ER strategies ∈ (3, 6, 9), and number of observations ∈ (30, 70, 100). We chose multiples of 3 for the number of ER strategies because there are three axes in the Lorenz System. When the number of ER strategies was 6 or 9, extra round(s) of resampling was performed from the same Lorenz System. We used the same values for the number of observations as we did in Simulation 1. We cross-tabulated the choices of values in three parameters to attain 45 unique profiles (an example profile has probability of switching = .10, 3 ER strategies, and 30 observations). We replicated each unique profile 1,000 times to generate 45,000 datasets in total. We generated the Lorenz System with the default values of lorenz function in *nonlinearTseries* package that produced points that lie on coordinates on three continuous dimensions (Garcia, 2022). In the first moment of each time series dataset, we sampled a point in the Lorenz System and used its coordinates as the ratings of ER strategies. Each following moment had a specified probability of switching to be sampled from a different wing. The resampling was repeated until a specified number of observations were generated in the dataset. A full overview of the simulation setup can be found in Supplemental Material 3.

ER Variability Indices and Data Analysis

Bray-Curtis dissimilarity and its two subcomponents nestedness and replacement were calculated using the *betapart* package (Baselga et al., 2022). Between-strategy *SD*, a moment-level index, was calculated as the *SD* across multiple strategies within one moment. Within-strategy *SD*, only available as a person-level index, was calculated as the *SD* of multiple scores across time within one strategy. For the analyses, we used the mean within-strategy *SD* across all strategies. Per definition, the between-strategy *SD* is calculated within a given moment and as such cannot capture changes in ER variability across time. To examine the performance of *SD*-based indices in moment-level temporal comparisons, we also included the successive difference of between-strategy *SD* (i.e., between-strategy *SD* of moment *t* minus between-strategy *SD* of the previous moment *t*-1, as proposed by for instance Aldao et al., 2015) .

Throughout this paper, we calculated ER variability indices in the main analyses using the successive difference approach. This approach is in line with the theoretical formulation of ER variability because it examines changes across time and takes temporal order into account (Kalokerinos et al., 2017). However, variability as the uniqueness of a moment – by inspecting how much it deviates from all other moments in the same individual – may be of importance when researchers are interested in within-person deviations from usual patterns, or in characterizing behavior at a certain time point or in a certain context. Thus, we also included this approach to comparison ("all-moment comparison"; see Supplemental Material 1) in the all analyses, which produced similar results as the successive difference approach (Supplemental Material 4). We examined the partial correlations[5] between the dataset-level mean of each ER variability index and all simulation parameters with the *ppcor* package (Kim, 2015).

Result and Discussion

Partial correlations between ER variability indices and simulation parameters showed that Bray-Curtis dissimilarity had high sensitivity in the expected direction to all parameters in both simulation studies (Table 2.2). First, Bray-Curtis dissimilarity was negatively associated with the autocorrelation parameter, indicating that the index was sensitive to instability in ER processes across time. Second, the index was positively associated with the within-strategy *SD* parameter, indicating that it was sensitive to greater dispersion in ER strategies across time. Third, as expected, the full index was not associated with the between-strategy correlation parameter. Importantly, upon partitioning, the replacement subcomponent was negatively associated with the between-strategy correlation parameter, indicating that it was able to detect changes in strategy switching. Conversely, the nestedness subcomponent was positively associated with the between-strategy correlation parameter, indicating that it was able to detect endorsement changes. Fourth, Bray-Curtis dissimilarity, specifically the replacement subcomponent and not the en-

5 We report partial correlations for our simulation studies because, by controlling for the shared variances on other parameters, the association between an index and a specific parameter is easier to evaluate. This allows for easier interpretation on to which parameter is an index sensitive to. Results of zero-order correlations are consistent with partial correlation results (see Supplemental Material 4).

dorsement subcomponent, was positively associated with the probability of switching parameter in Simulation 2. Finally, the full Bray-Curtis dissimilarity index was not related to study design parameters (i.e., number of ER strategies and observations). However, the two subcomponents were influenced by the number of ER strategies: a higher number of ER strategies was associated with higher replacement and lower nestedness. This may complicate comparing the subcomponents across studies with different numbers of ER strategies.

Comparatively, the benchmark between-strategy and within-strategy SD-based indices had undesirable properties. The between-strategy SD, of a certain moment or in temporal comparison, correlated positively with the between-strategy correlation parameter in Simulation 1, indicating that it overrepresented strategy switch but underrepresented endorsement change. Additionally, it was not correlated with the probability of switching in Simulation 2, indicating that between-strategy *SD* did not detect ER variability primarily introduced by strategy switching. The within-strategy *SD* had no association with the between-strategy correlation parameter in Simulation 1; however, unlike the subcomponents of Bray-Curtis dissimilarity, it cannot distinguish how strategy switching and endorsement change processes are affected by the correlation between ER strategies. The within-strategy *SD* was only weakly associated with the probability of switching parameter in Simulation 2. These limitations are expected because within-strategy *SD* is methodologically limited to the person-level thus cannot assess moment-level variability across strategies.

Results from two simulations favored Bray-Curtis dissimilarity in perfect measurement conditions, namely continuous data collected without any missing observations. ESM studies with human subjects, however, typically contain missing data and often make use of Likert-type scales. Those scales result in a loss of true variance due to scale-mapping (e.g., a true score of 1.222 would be forced to a become a 1 on an integer scale). To check the robustness of the results in heterogeneous measurement conditions, we conducted sensitivity analyses for the index's performance on degrees of completely-at-random missingness up to 50% and on different rounding precisions (the fewer decimal places in rounding, the coarser the scale-mapping process is, and there is more loss of true variance). Procedures and findings of these sensitivity analyses are available in Supplemental Material 5. Bray-Curtis dissimilarity remained sensitive to simulation parameters despite minor decreases in the strength of association compared to our main simulations results. The general conclusion was that Bray-Curtis dissimilarity remained robust in detecting ER variability across different conditions of missingness and scales.

Table 2.2

Summary of Influences of Simulation Parameters on Two Processes of Emotion Regulation (ER) Variability and the Partial Correlations between Parameters and ER Variability Indices

	Simulation 1 parameters					Simulation 2 parameters		
	ρ_{auto}	σ	ρ_{cor}	N_{ER}	n	p_{switch}	N_{ER}	n
ER variability index	**Theorized or ideal directions of association**							
Strategy switching	-	+	-	0	0	+	0	0
Endorsement change	-	+	+	0	0	0	0	0
ER variability index	**Partial correlation**							
Within-strategy *SD*	-.44	.98	.00	.00	.02	.19	.00	.07
Between-strategy *SD*	-.27	.96	-.82	.52	-.03	.02	.06	.00
Between-strategy *SD* successive difference	-.24	.89	-.59	-.78	-.01	.02	-.89	.00
Bray-Curtis dissimilarity	-.80	.97	.01	.00	-.03	.88	.01	-.01
Replacement subcomponent	-.41	.80	-.79	.64	-.01	.88	.66	.00
Nestedness subcomponent	-.52	.88	.74	-.58	-.02	.02	-.83	-.02

Note. -: negative associations; +: positive associations; 0: no associations; ρ_{auto}: autocorrelation; σ: within-strategy *SD,* adjusted with a correction factor because the *SD* is inflated when autocorrelation is high (Beran, 1994); ρ_{cor}: correlation between strategies; N_{ER}: number of ER strategies; n: number of observations; p_{switch}: probability of switching.

To summarize results from the two simulations: In line with expectations, Bray-Curtis dissimilarity demonstrated better sensitivity than *SD*-based indices towards varying levels ER variability. The full Bray-Curtis dissimilarity index was unaffected by the number of ER strategies and number of observations and maintained its performance in sensitivity analyses that tested different degrees of variance loss and missingness, suggesting it is applicable across a wide range of study designs and conditions. Importantly, partitioning the full index into replacement and nestedness subcomponents captured the strategy switching and endorsement change processes that are hypothesized to play a central role in ER variability.

PART II: TEMPORAL PREDICTIVE VALIDITY OF NEW ER VARIABILITY INDICES: A REANALYSIS

After showing that Bray-Curtis dissimilarity is sensitive to the hypothesized ER variability processes, we evaluated its predictive validity in empirical data. Based on the idea that ER variability plays a central role in well-being (Aldao et al., 2015), we examined the consistency and predictive power of different ER variability indices on predicting NA in three published ESM datasets previously used to study the same research question (Blanke et al., 2020). We expected that higher ER variability would be associated with lower NA at both the moment- and person-level, with Bray-Curtis dissimilarity showing higher consistency and predictive power for NA compared to *SD*-based indices.

Method

Procedure and Participants

Information regarding each dataset is summarized in Table 2.3. The three datasets were part of larger studies and sample sizes were set by their respective principal investigators. Participants in all studies took part in laboratory sessions in which they gave informed consent and received standardized devices with ESM data collection software. Each study received approval of its respective ethical committee. Further details of participants and procedures can be found in the original publication (Blanke et al., 2020). We obtained the authors' consent in reusing their data, which are publicly available at https://osf.io/mxjfh/.

Measures

Questionnaires. All datasets assessed NA items and ER strategies at each ESM observation (Table 2.3). Raw scores were rescaled to range from 0 to 6 prior to analyses to harmonize datasets. Affect items were selected from the PANAS scales (Watson et al., 1988) in dataset 1 and based on the circumplex model of affect (Russell, 1980) in datasets 2 and 3. ER strategies were chosen from different stages of the process model of ER (Gross, 2015) to fit the research questions of the parent studies. Dataset 1 had items about attentional deployment (reflection, rumination, distraction). Datasets 2 and 3 included strategies about attentional deployment, cognitive change (reappraisal) and response modulation (expressive suppression, social sharing).

Indices. We calculated moment-level NA as the mean of all affect items at each moment. For ER variability indices, we calculated Bray-Curtis dissimilarity (the moment-level full index, plus its replacement and nestedness subcomponents) and the *SD*-based indices: moment-level between-strategy *SD*, moment-level between-strategy *SD* successive difference, and person-level within-strategy *SD*. In contrast to the simulation studies, where mean ER strategy ratings were the same for all datasets, mean ER strategy ratings in the empirical datasets were different between participants. Given that the mean and *SD* are often confounded when bounded rating scales are used, we standardized *SD*-based indices by their maximum possible values given a mean level of ER (relative *SD*; Mestdagh et al., 2018). We did not apply a similar transformation for Bray-Curtis dissimilarity because it already controls for the mean by having the sum of all ratings at its denominator.

Table 2.3

Overview of ESM Datasets Included in Empirical Analysis

Dataset	**1**	**2**	**3**
Country of data collection	Germany	Belgium	Belgium
Participants: *N*	70	95	200
Gender: % female	50.0%	62.1%	55.0%
Age: *M* (*SD*)	25.55 (2.74)	19.06 (1.28)	18.32 (0.96)
ESM study duration in days	9	7	7
Observations per day	6	10	10
Number of observations per participant: *M* (*SD*)	54.4 (3.25)	60.3 (4.60)	61.5 (6.30)
Compliance	98.3%	86.1%	87.8%
Response scale (applies to both negative affect and ER strategy items)	7-point Likert-style from 0 (*does not apply at all*) to 6 (*applies strongly*)	Slider scale from 1 (*not at all*) to 100 (*very much*)	Slider scale from 0 (*not at all*) to 100 (*very much*)
Negative affect items	Nervous Downhearted Distressed	Angry Sad Anxious Depressed	Angry Sad Anxious Depressed
Reference frame for negative affect items	Since waking up/ since the last assessment	Current (at the time of assessment)	Current (at the time of assessment)
ER strategy items	Rumination on thoughts Rumination on feelings Distraction from thoughts Distraction from feelings Reflection on thoughts Reflection on feelings	Rumination Distraction Reflection Other perspective/ reappraisal Expressive suppression Social sharing	Rumination about the past Rumination about the future Distraction Other perspective/ reappraisal Expressive suppression Social sharing
Reference frame for ER strategy items	Since waking up/ since the last assessment	Since the last assessment	Since the last assessment

Note. ESM = experience sampling method; ER = emotion regulation. In Dataset 1, participants could continue the study up to a duration of 12 days to meet the target number of observations.

A moment with ER strategies all rated 0 gave undefined Bray-Curtis dissimilarity and relative between-strategy *SD*. Additionally, indices in successive differences were unavailable if there were missingness or all-zero ratings in ER strategies in a moment or the previous moment. We were able to calculate variability indices in 82.0% to 97.5% of the moments with complete ER strategy ratings (see Supplemental Material 6 for details). Moments with unavailable indices were excluded from respective multilevel model analyses.

Data Analysis

We used multilevel models to examine whether ER variability indices predicted NA at the moment-level and person-level, where observations (Level 1) were nested within persons (Level 2). We separated ER variability indices of each moment into within-person and between-person components. The within-person component, obtained by person-mean centering, is a moment-level predictor that reflects the moment-to-moment fluctuation of the variable relative to that person's average. The between-person component, obtained by subtracting the within-person component from the grand-mean centered score , is a person-level predictor that reflects how much the person differs relative to the overall study population's average. NA at each moment was predicted by the within-person and between-person components of ER variability indices at Level 1. Moment-level predictors were entered as both fixed and random effects. Random intercepts and slopes were allowed to covary. Person-level predictors were entered as fixed effects. In the analysis, we added the assessment number (time) as a covariate to control for any systematic temporal trends in the data. We included a first-order autocorrelation structure on residuals. We analyzed each ER variability index separately, except for the two Bray-Curtis dissimilarity subcomponents, which we analyzed together. We used the *nlme* package (Pinheiro et al., 2022) with the "optim" modeling optimizer to estimate multilevel models. To assess the predictive power of models, we drew 1000 bootstrapped samples from each dataset with the *boot* package (Canty & Ripley, 2021) to obtain a stable estimate of the root mean squared error (RMSE) of these models with the *performance* package (Lüdecke et al., 2021).

Result and Discussion

Descriptive Analyses

At 96% (range: 94% to 97%) of the completed prompts, participants reported to have used at least one ER strategy since the last prompt. The intraclass correlation coefficients for moment-level NA and ER strategies ranged from .40 to .55, for Bray-Curtis dissimilarity from .30 to .43, for between-strategy *SD* from .45 to .49, for replacement from .12 to .22, and for nestedness from .06 to .09. See Supplemental Material 6 for other descriptive statistics.

Moment-Level Associations between ER Variability Indices and NA

Results of the multilevel modeling using different ER variability indices to predict NA are shown in Table 2.4. Analyses showed that the between-strategy *SD* at a certain moment was a significant predictor of NA in dataset 1 only. The between-strategy *SD* in temporal comparison was a significant predictor of NA in dataset 3 only. The full Bray-Curtis dissimilarity index predicted lower momentary NA in all three datasets, indicating that when individuals varied more in ER strategy use, they experienced lower NA. When examining the subcomponents of Bray-Curtis dissimilarity, replacement was related to less momentary NA in all three datasets, whereas nestedness was only a significant predictor in dataset 1. As such, strategy switching was a more consistent moment-level predictor of decreased NA than endorsement change. Overall, fixed effect results confirmed that Bray-Curtis dissimilarity had better consistency than the between-strategy *SD* in predicting momentary NA[6].

Person-Level Associations between ER Variability Indices and NA

The within-strategy and between-strategy *SD* indices (with or without temporal comparisons) were associated with less NA at the person level in two of the three datasets. As was the case with the momentary analyses, the full Bray-Curtis dissimilarity index was associated with lower NA at the person level in all three datasets, indicating that individuals who showed more variation in ER strategy use across time also reported lower NA on average. When examining the subcomponents of Bray-Curtis dissimilarity, replacement (reflecting strategy switching) was related to lower average NA in all datasets, whereas nestedness (reflecting endorsement change) was related to lower NA in datasets 2 and 3 only. Overall, results confirmed that Bray-Curtis dissimilarity associated more consistently than the *SD*-based indices with NA at the person level.

Predictive Power of ER Variability Indices on NA

A lower RMSE of a model indicates higher predictive power. As shown in Table 2.5, mean RMSEs from Bray-Curtis dissimilarity models on the bootstrapped samples were consistently lower than RMSEs from *SD*-based models in all three datasets. The results confirmed our expectation that Bray-Curtis dissimilarity would have higher predictive power compared to the *SD*-based indices. However, RMSEs differences were small. This indicated that there were no substantial gains in predictive power from using Bray-Curtis dissimilarity instead of *SD*-based indices.

6 At an anonymous reviewer's request, we also examined the moment- and person-level relationships between NA and ER variability indices based on raw or unstandardized SDs (instead of relative SD). These SD-based indices remained less consistent than Bray-Curtis dissimilarity in predicting NA, and sometimes produced results that were difficult to interpret (e.g., positively predicting subsequent NA), which could be due to a nonlinear relationship between mean and variance (for discussion, see Mestdagh et al., 2018). See Supplemental Material 7 for details.

Table 2.4

Multilevel Results on Moment-Level and Person-Level Components of Emotion Regulation (ER) Variability Indices in Predicting Negative Affect in Three Datasets

	Fixed effect (Standard error)					
	Moment-level results			**Person-level results**		
	Dataset			Dataset		
ER variability index	1	2	3	1	2	3
Within-strategy *SD*	(no moment-level results)			-2.35** (0.79)	-0.59 (0.58)	-0.70* (0.27)
Between-strategy *SD*	-0.33* (0.13)	0.11 (0.08)	0.05 (0.06)	-3.44*** (0.54)	-0.25 (0.39)	-0.53** (0.17)
Between-strategy *SD* successive difference	-0.01 (0.12)	-0.08 (0.07)	0.15** (0.05)	0.28 (1.59)	-3.94** (1.32)	-1.49* (0.72)
Bray-Curtis dissimilarity	-0.44*** (0.12)	-0.18** (0.06)	-0.12** (0.04)	-1.58* (0.65)	-1.92*** (0.29)	-1.58*** (0.17)
Replacement	-0.41** (0.14)	-0.23** (0.08)	-0.13** (0.04)	-2.75* (1.23)	-1.77** (0.56)	-1.21*** (0.28)
Nestedness	-0.38* (0.16)	-0.08 (0.08)	-0.03 (0.04)	-1.71 (1.46)	-2.94** (1.09)	-3.11*** (0.51)

Note. Moment-level results are based on the within-person component, person-level results are based on the between-person component. Within-strategy and between-strategy *SD* were calculated with relative *SD* (Mestdagh et al., 2018). To calculate within-strategy *SD*, a person-level index, the mean *SD* across all strategies was used. Fixed effect and random effect of intercept and time factor, random effect of the variability indices, autoregressive error-structure, and covariances between intercept and slopes were estimated but are not displayed.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2.5

Means of Root Mean Squared Error (RMSE) of Multilevel Models of Emotion Regulation (ER) Variability Indices Predicting Negative Affect in Bootstrapped Samples from Three Datasets

	Unstandardized RMSE		
	Dataset		
ER variability index	1	2	3
Within-strategy *SD*	0.881	0.654	0.594
Between-strategy *SD*	0.846	0.635	0.577
Between-strategy *SD* successive difference	0.858	0.648	0.581
Bray-Curtis dissimilarity (full index)	0.837	0.631	0.572
Bray-Curtis dissimilarity (subcomponents)	0.827	0.627	0.569

Note. We bootstrapped each dataset 1000 times to produce the above mean RMSEs. Within-strategy and between-strategy *SD* were calculated with relative *SD* (Mestdagh et al., 2018).

GENERAL DISCUSSION

ER variability refers to changes in the use of ER strategies across time and is increasingly being studied in daily life (Aldao et al., 2015). According to the theoretical framework of ER variability, there are two central processes in ER variability: switching between ER strategies, and changes in overall endorsement in ER strategies. In the present paper, we argue that current approaches to ER variability in ESM data – calculating the *SD* within strategies across time (within-strategy *SD*) and between strategies at one time-point (between-strategy *SD*) – cannot capture these central processes and as such lack construct validity. Here, we propose Bray-Curtis dissimilarity as an ER variability index and argue it is in line with the theoretical framework of ER. Through simulation studies, we demonstrated that Bray-Curtis dissimilarity, compared to *SD*-based indices, is superior in capturing ER variability and its two constituent processes, especially when ER variability was primarily driven by strategy switching. Additionally, using empirical ESM data, we showed that Bray-Curtis dissimilarity was related to less NA at both the moment- and person-level, indicating that greater variation in ER strategies across time is related to lower NA, with better predictive validity than *SD*-based approaches. In summary, Bray-Curtis dissimilarity is a promising index for estimating ER variability in time-series data.

One advantage of using Bray-Curtis dissimilarity is that researchers can choose to investigate the strategy switching versus endorsement change in ER variability through the two subcomponents of replacement and nestedness. In ecology, partitioning Bray-Curtis dissimilarity has led to breakthroughs in identifying different processes that contributed to biodiversity variability (Baselga et al., 2012). Partitioning Bray-Curtis dissimilarity holds similar promise for estimating ER variability. Our re-analysis already provided some indication that the two ER processes have different implications: strategy switching contributed more consistently to the association between ER variability and NA than endorsement change in daily life. Importantly, the ability to disentangle these processes leads to new future research questions for the field of ER variability: Does strategy switching contribute more to psychological health than endorsement change in daily life? How are the two processes differentially influenced by other factors? For example, it is plausible that endorsement change is less likely upon the experience of fatigue (Grillon et al., 2015) and strategy switching is guided by the intensity of NA (Birk & Bonanno, 2016).

Constraints on Generality

There are limitations that constrain the generality of our findings. First, our simulation studies were limited by assumptions in our data generation process. We assumed a multivariate normal distribution in VAR(1); we tested strategy switching by resampling the Lorenz system, which has only two clusters of observations. Data generated under these assumptions may not resemble those collected from human subjects. As such, the sensitivity of the indices tested may not be the same when other conditions are imposed.

Nevertheless, our goal here is not to correctly represent all aspects of complex ER dynamics, but to test Bray-Curtis dissimilarity against other indices in detecting multivariate variability across time. If an index does not perform well in these simple and well-defined conditions, it will not perform well in real data which are more complex. Our findings offer an initial demonstration of the advantages that Bray-Curtis dissimilarity has over *SD*-based indices. Future research can explore how Bray-Curtis dissimilarity compares to other ER variability indices in a fuller set of study parameters and distributional assumptions (e.g., non-normality).

Second, we conducted sensitivity analyses on two types of measurement conditions in straightforward manners, namely rounding continuous data in different decimal places and introducing completely-at-random missingness. In human subjects research, there are other facets of heterogeneity in measurement conditions. These may include various intensities and types of measurement noise, comprehensiveness of ESM measures (i.e., the model of ER had six strategies, but the study design had only measured five), and idiosyncrasy of repertoire of ER strategies. While we acknowledge measurement issues may undermine the sensitivity of indices, with current results, we believe such issues should not critically affect the choice of indices that match our theoretical premises. Further investigation as to how measurement conditions affect different indices is worthwhile but out of scope for the current paper.

Third, although a more theory-aligned means of quantifying ER variability (Aldao et al., 2015), Bray-Curtis dissimilarity showed only modest improvements over *SD*-based indices in predicting the real-world outcome of decreases in NA. Similar RMSEs between Bray-Curtis dissimilarity and *SD*-based indices are understandable given the positive intercorrelations that have been observed among many measures of affect dynamics (Dejonckheere et al., 2019). Further, even minor RMSE improvements are encouraging considering Bray-Curtis dissimilarity's added advantages in detecting the theoretically relevant ER processes of strategy switching and endorsement change (Aldao et al., 2015) along with its consistently significant fixed effect in predicting NA (as opposed to the *SD*). Broadening the discussion, NA is just one of the many outcomes that might be related to ER variability. For example, between-strategy ER variability was found to associate with depressive symptoms (Wang et al., 2021). Future research may reexamine these relationships using Bray-Curtis dissimilarity to better ascertain the predictive power of the new index and its added advantages in quantifying constituent processes underlying the variability.

Fourth, the participants in the empirical studies we reanalyzed were primarily young adults from Western, educated, industrialized, rich, and democratic (WEIRD; Henrich et al., 2010) background with relatively low negative emotion intensities. As such, current results about ER variability predicting NA may not generalize to non-WEIRD or clinical populations. However, this constraint on generalizability only pertains to the predictive validity, and we have no reason to expect that Bray-Curtis dissimilarity would work differently in these populations in estimating their ER variability.

Three Recommendations for Using Bray-Curtis Dissimilarity to Estimate ER Variability

We have three recommendations to researchers who plan to use Bray-Curtis dissimilarity to study ER variability. The first recommendation is about dealing with missing ESM data. When data are incomplete, Bray-Curtis dissimilarity is not available for the moments following missingness. While the degree of missingness did not impair the usefulness of Bray-Curtis dissimilarity (see Supplemental Material 5), researchers have the option of imputing missing data in these multivariate time series data (Asparouhov et al., 2018). Alternatively, researchers could estimate Bray-Curtis dissimilarity by how much the moment of interest deviates from all other moments in the same individual (Supplemental Material 1). This all-moment comparison approach demonstrated similar performance as the successive difference approach in the main analyses (Supplemental Material 4) and may be particularly useful when missingness is high.

The second recommendation concerns the choice of ER strategies in study design, which determines the generalizability of conclusions based on ER variability. If only a narrow range of ER strategies is included, the resultant ER variability would then provide an incomplete representation of the participants' changes across time in using ER strategies. For example, in Edmund's example, the ER variability as calculated in Table 2.1 only describes the changes in distraction and social sharing. The ER variability across the six time points would be different by including other ER strategies Edmund used (e.g., reappraisal) in the calculation. Therefore, researchers who are interested to capture ER variability of the full ER process are recommend to include a broader range of maximally diverse ER strategies based on the ER theoretical frameworks they adopt.

The third recommendation is to always interpret a subcomponent of Bray-Curtis dissimilarity in the context of the other subcomponent. Not doing so is especially problematic for the nestedness subcomponent, because its value is mathematically dependent on the replacement subcomponent (MacGregor-Fors et al., 2022). Therefore, even when research interests lie in a specific ER variability process (e.g., how endorsement change is affected by mental fatigue), we recommend that researchers always report the full Bray-Curtis dissimilarity and conduct analyses using both the full and partitioned Bray-Curtis dissimilarity.

Advancing ER Theory: Inspirations from Ecology

Theories of ER may be advanced by further examining how ecologists interpret biodiversity variability as estimated by Bray-Curtis dissimilarity. Ecologists have explained biodiversity variability in terms of competition between species and change in habitat (R. J. Lewis et al., 2016). In other words, ecologists infer mechanisms that drive variability within the context of the environments in which species are situated (Heino et al., 2015). Analogously, researchers should study ER strategies and ER variability within the context of the circumstances in which ER happens. For instance, there are some indications that reappraisal – an ER strategy aimed to reframing one's thoughts about a certain event – is only adaptive in uncontrollable situations (Troy et al., 2013). Aldao et al. (2015) noted that high ER variability can refer to either flexibility or instability, depending on how ER changes are mapped onto the context at each moment. As such, an important next step is to use Bray-Curtis dissimilarity to understand ER flexibility, by testing how ER variability associates with changes in contextual factors, such as presence of others or appraisal of situation (for an overview of analytical techniques see English & Eldesouky, 2020).

More broadly, our proposal to estimate ER variability using Bray-Curtis dissimilarity joins other work that applies ecological concepts to psychological processes. A first example comes from research on individual differences in emotional diversity (emodiversity). Diversity in ecology refers to both the variety and relative amounts of organisms in an ecosystem (Legendre & Legendre, 2012). In emotion research, emodiversity refers to the range and evenness of emotions experienced over time. Higher emodiversity has been associated with fewer depressive and physical health symptoms independent of mean emotion frequencies (Quoidbach et al., 2014; but see Brown & Coyne, 2017 for criticisms). A second example comes from research that uses complex system approaches to analyze within-person changes in psychopathology. The complex systems approach has been inspired by ecology, where increasing autocorrelation and variance in population in an ecosystem have been found to be early warning signals prior to major population change. In psychopathology, autocorrelation and variance in self-rating of negative affect and fluctuations in daily self-ratings of the therapeutic process have been suggested to be early warning signals for sudden improvement or deterioration of psychopathology in patients with mood disorders (Helmich et al., 2021; Olthof et al., 2020; van de Leemput et al., 2014; Wichers et al., 2016, 2020).

Applying Bray-Curtis Dissimilarity to Understand Other Dynamic Processes

Beyond the study of ER processes, Bray-Curtis dissimilarity may be useful in estimating variability in other multivariate time series data. Emotion variability is one of such possibilities. Emotion variability is often studied in terms of a single emotion or by aggregating across emotions based on valence (i.e., taking means of negative or positive emotions to obtain estimates of NA and PA) before applying indices, such as the *SD* or mean squared successive difference, to quantify their dynamics across time (see Dejonckheere et al., 2019 for an overview). Both considering a single emotion and aggregating across emotions ignore how emotions change in relation to one another over time (see review by

McKone & Silk, 2022). These practices emphasize overall change in emotion intensity but cannot capture more complex dynamics such as switching from experiencing one emotion to another. Bray-Curtis dissimilarity is a promising alternative to already existing methods in detecting emotional switching: Firstly, it can handle ordinal-continuous data, which is in contrast to Houben et al. (2016)'s method that recodes ordinal-continuous data into binary. Secondly, Bray-Curtis dissimilarity is a moment-level index applicable to multiple emotions, which is an improvement to a previously proposed person-level index that can only handle two emotions (Dejonckheere et al., 2018). Emotional switching is just one example, and we are optimistic that Bray-Curtis dissimilarity will prove useful in investigating the patterns of dynamics in yet other types of multivariate time series data.

Conclusion

ER variability, the change in using ER strategies across time, is necessary for adapting to changing situational needs and thus has implications for mental health. This paper proposes Bray-Curtis dissimilarity as a theory-informed index for estimating moment-level ER variability that improves upon the common operationalization of within- and between-strategy *SD*. Through simulation studies, we showed Bray-Curtis dissimilarity has better sensitivity than *SD*-based indices in detecting the constituent ER variability processes of strategy switching and endorsement change. Additionally, using data from three ESM studies, we demonstrated that Bray-Curtis dissimilarity is more consistently related to NA in the expected direction than *SD*-based approaches. The new index enables researchers to study ER variability with higher conceptual and methodological precision, leading to an array of new research questions, and paving the way for further advancements in understanding ER and other dynamical processes.

3

Emotion Differentiation in Adolescents: Short-term Trade-offs with Regulation Variability and Emotion Intensity

This chapter is based on:
Lo, T. T., Verhagen, M., Pouwels, J. L., van Roekel, E., O'Brien, S. T., Debra, G., Braet, J., Vink, J. M., & Maciejewski, D. F. (2025). Emotion Differentiation in Adolescents: Short-term Trade-offs with Regulation Variability and Emotion Intensity. *Affective Science*, 1-16. https://doi.org/10.1007/s42761-025-00301-4

ABSTRACT

Emotion differentiation—distinctively labeling emotions—is theorized to guide adolescents in regulating emotions amid changing daily-life situations. Momentary fluctuations in emotion differentiation are expected to introduce variability in using emotion regulation strategies, leading to sequential emotion intensity changes. Using five experience sampling datasets (N = 750, aged 11–25, 59.17% female, 25,834 observations) that repeatedly assess emotion differentiation and emotion regulation variability, we examined their interaction and impact on emotion intensity. Surprisingly, moments of heightened emotion differentiation were followed by more stable use of regulation strategies (lower variability), while moments of higher emotion regulation variability were followed by less emotion differentiation. Both heightened differentiation and regulation variability preceded contra-hedonic outcomes, such as increased negative emotions and decreased positive emotions. These findings were robust across different types of emotion regulation variability (intensity or switching) and valences of emotions (positive or negative). In the short term, emotion differentiation predicts reduced regulation variability and may bring unpleasant changes in emotion intensity.

Keywords: Dynamics, Emotion Differentiation, Emotion Regulation Variability, Emotion Intensity, Adolescents

EMOTION DIFFERENTIATION IN ADOLESCENTS: SHORT-TERM TRADE-OFFS WITH REGULATION VARIABILITY AND EMOTION INTENSITY

Adolescence[1] is a period of emotional challenges ranging from pubertal changes, academic or work-related pressure, and transforming interpersonal relationships (Holmbeck et al., 2006). To navigate this transitional period, adolescents use various strategies to regulate the intensity of their emotions (Klein et al., 2022). Emotion differentiation – how well emotions are distinctively labelled – is expected to facilitate emotion regulation, because knowing what one feels informs ways of regulating one's emotions (Barrett et al., 2001; Berking & Whitley, 2014; Schwarz & Clore, 1983). Based on this assumption, fluctuating levels of emotion differentiation within an adolescent should introduce subsequent variability in use of emotion regulation strategies and, sequentially, changes in emotion intensity (Kashdan et al., 2015). In the background of these theoretical views, there are increasing interests to develop self-guided and online interventions that target emotion differentiation for improving emotion regulation (Matt et al., 2024; Seah & Coifman, 2024; Van der Gucht et al., 2019). Before it becomes appropriate to target emotion differentiation in interventions, we need to clarify the two theorized effects of emotion differentiation on emotion regulation variability and emotion intensity changes in adolescents' daily lives, which remain empirically understudied. Therefore, this study aims to investigate the temporal sequences between adolescents' emotion differentiation and emotion regulation variability in their daily lives, and the subsequent changes in emotion intensity therein.

Is Emotion Differentiation Related to Emotion Regulation Strategy Use in Daily Life?

To study the relation between emotion differentiation and emotion regulation in daily life, researchers often assess emotions and emotion regulation strategies repeatedly over the course of several days, for instance using daily diaries or experience sampling methods (ESM). These methods have two advantages, namely capturing life as it is lived with high ecological validity, and allowing researchers to tease apart within-person fluctuations from individual differences of the baseline emotion (regulation) throughout the assessments (Bolger & Laurenceau, 2013).

Using these methods, researchers have investigated how emotion differentiation is related to emotion regulation strategy use. Two studies that investigated this association between individuals gave an inconclusive picture. One daily diary study found that individuals with higher differentiation of negative emotions showed greater average use of emotion regulation strategies compared to those with lower emotion differentiation

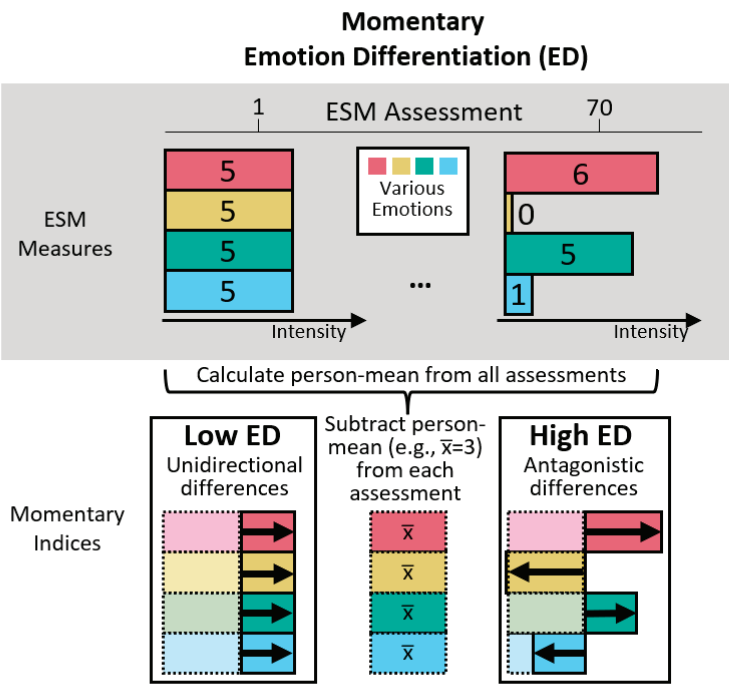
1 We followed a recent definition of adolescence as ages 10 to 25 (Sawyer et al., 2018).

(Barrett et al., 2001), but an ESM study that examined separate strategies found that high differentiators used less social sharing compared to low differentiators (Kalokerinos et al., 2019). Additionally, this ESM study revealed no significant associations between emotion differentiation and five other strategies examined (e.g., distraction).

ESM allows researchers to scrutinize daily-life within-person fluctuations of emotions and their regulation. However, similar to studies in individual difference, there lacks empirical evidence on within-person temporal relations from emotion differentiation to emotion regulation strategy use. A 10-day ESM study showed that on days when university students had higher negative emotion differentiation than usual, they did not use their emotion regulation strategies any differently compared to their average use (O'Toole et al., 2021). Using a recently developed within-person momentary emotion differentiation index (Figure 3.1, Erbas et al., 2021), one study tested if emotion differentiation preceded emotion regulation: Lower emotion differentiation predicted subsequent higher social sharing. However, this finding was only seen in two out of four datasets analyzed (Sels et al., 2024). Overall, empirical evidence suggests weak between-person associations between emotion differentiation and the use of separate emotion regulation strategies, and potentially no concurrent or temporal within-person associations.

Figure 3.1

Hypothetical assessments of ESM measures to illustrate how to calculate emotion differentiation.



Note. For simplicity, only the calculation steps of the numerator but not the denominator are shown. Numbers on the bars represent the intensity ratings of emotions.

The Need To Consider Variability of Multiple Emotion Regulation Strategies Collectively

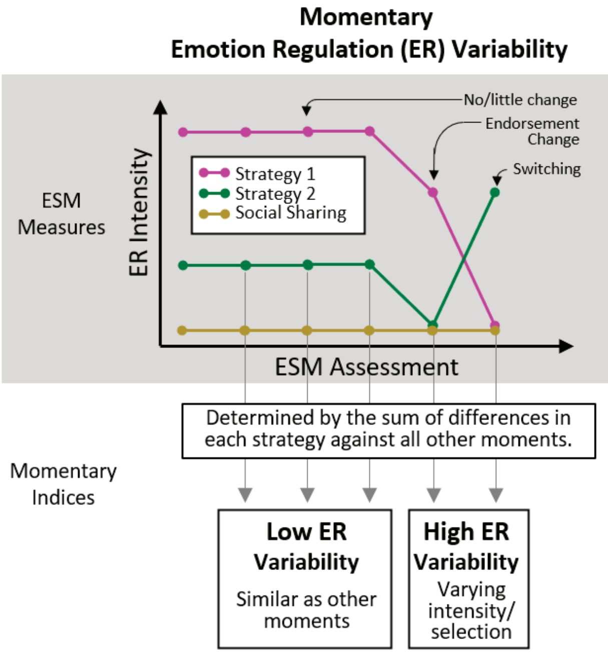
These weak associations may have been a result of a methodological limitation, namely analyzing the variability of emotion regulation strategies separately. Hypothetically, imagine an adolescent who consistently not used social sharing but alternated between using two other strategies throughout all measurements (Figure 3.2). Researchers who only analyze the adolescent's social sharing would, by their decision of analyzing a single strategy, miss out variability from the two other strategies. Simulation studies have demonstrated the poor performance of this approach of single-strategy analysis in detecting emotion regulation variability, even if the approach is mitigated by taking the average variability from multiple single-strategy analyses (Lo et al., 2024). Therefore, emotion regulation variability should be considered between multiple strategies *collectively* across time. A recently validated method for capturing emotion regulation variability is the Bray-Curtis dissimilarity index, which has been commonly used in ecological research to quantify compositional changes in multiple species over sites. Applied to emotion regulation, treating each ESM assessment as a site and regulation strategies as species, Bray-Curtis dissimilarity denotes the degree to which use of strategies at a moment of interest is different from other moments. The Bray-Curtis dissimilarity full index can be partitioned into two subcomponents that reflect two theoretical grounded processes of emotion regulation variability: Strategy switching (e.g., replacing one strategy with another) and endorsement change (e.g., decreasing the extent of emotion regulation). Bray-Curtis dissimilarity has an advantage over conventional variability indices (e.g., standard deviation) in detection of momentary within-person emotion regulation variability in all strategies (Lo et al., 2024). This momentary index can be averaged within a person. Such trait-like emotion regulation variability is theorized to be the foundation of adaptively using emotion regulation strategies to match situational demands (Aldao et al., 2015). To overcome the previous methodological limitation of examining strategies separately, we reexamined whether emotion differentiation affects subsequent use of multiple emotion regulation strategies using the Bray-Curtis dissimilarity index.

Changes in Emotion Intensity: Feeling Better or Worse?

Adolescents endorse emotion regulation strategies to change the perceived intensity of emotions. If emotion differentiation is to facilitate emotion regulation, a subsequent change in emotion intensity should follow. Typically, emotion regulation is assumed to produce pro-hedonic outcomes—decreasing negative emotions and increasing positive emotions (Webb et al., 2012). Evidence supports this pro-hedonic effect in both individual differences and within-person fluctuations in emotion differentiation. For individual differences, adolescents with high emotion differentiation appear buffered from depressed feelings when experiencing stress (Nook, Flournoy, et al., 2021) or rumination (Starr et al., 2017). At the within-person level, momentary emotion differentiation is positively associated with simultaneous pro-hedonic outcomes (Erbas et al., 2021). Emotion regulation strategies also play a role in the differentiation-intensity link; individuals with higher baseline negative emotion differentiation can reduce negative emotions with less strategy deployment compared to those with lower differentiation (Kalokerinos et al., 2019). Integrating this evidence with theoretical models of emotion differentiation (Kashdan et al., 2015), we test a within-person mediation model, where emotion differentiation influences emotion intensity change through emotion regulation.

Figure 3.2

Hypothetical assessments of ESM measures to illustrate how to calculate emotion regulation variability.



Note. For simplicity, only the calculation steps of the numerator but not the denominator are shown.

Building on previous findings, one might speculate that heightened emotion differentiation and emotion regulation variability would lead to pro-hedonic changes in emotion intensity (i.e., decreases in negative emotions and increases in positive emotions). However, it is equally plausible that contra-hedonic outcomes—such as increases in negative emotions and decreases in positive emotions—could result instead. Psychotherapy literature recognizes that emotion differentiation, a common therapeutic task across different treatment approaches (Sønderland et al., 2023), intensifies negative emotions elicited in therapy (Lane et al., 2022). Similar short-term contra-hedonic outcomes appear in non-clinical samples. In one experiment with university students who feared spiders, participants assigned to a condition that put their feelings into words - a procedure related to increase of baseline emotion differentiation (Seah & Coifman, 2024) - demonstrated reduced physiological fear arousal and improved approach behaviors only after a week, but not immediately (Kircanski et al., 2012). In another experiment, students who explored their emotions in previous upsetting experiences and wrote about them showed immediate spikes in negative emotion (Pascual-Leone, Yeryomenko, et al., 2016). Complicating the expectation of pro- or contra-hedonic outcomes, an ESM study showed that attention to emotion is associated with high negative emotion intensity concurrently but preceded subsequent decreases in intensity (Thompson et al., 2011); Assuming attending to emotions is a prerequisite for emotion differentiation, the contribution of emotion differentiation to subsequent changes in emotion intensity likely depends on how long attention is sustained.

Based on this evidence, we remained open to both short-term pro-hedonic and contra-hedonic changes in emotion intensity when examining whether emotion differentiation affects subsequent emotion intensity via emotion regulation variability.

The Present Study

Our study tested the temporal relations between emotion differentiation and emotion regulation variability, and their effect on subsequent emotion intensity within adolescents. In all our analyses, we focused solely on negative emotion regulation strategies, as there were limited datasets available that measured positive emotion regulation strategies, preventing us from testing similar hypotheses with sufficient statistical power.

In line with the idea that emotion differentiation facilitates emotion regulation, which we expected to lead to changes in strategy use (i.e., increases in variability), we pre-registered three hypotheses: Hypothesis 1 states that, within an adolescent, greater emotion differentiation at a given moment is related to higher emotion regulation variability at the subsequent moment. Previous theoretical discussions did not expect a reversed temporal sequence (Kashdan et al., 2015; Thompson et al., 2021). Therefore, Hypothesis 2 states that, within an adolescent, emotion regulation variability at one moment is not associated with emotion differentiation at the following moment. Hypothesis 3 is between-person, stating that adolescents with higher emotion differentiation would show higher emotion regulation variability on average. After analyzing the results from these hypotheses, we formulated the following exploratory research questions: Research question 1 explores whether within-person fluctuations in emotion differentiation and emotion regulation variability precede subsequent pro-/contra-hedonic changes in emotion intensity. Additionally, research question 2 explores if the differentiation-intensity temporal relation, if any, is mediated by emotion regulation variability.

All pre-registered hypotheses and research questions concerned differentiation of *negative* emotions because previous literature mostly investigated negative emotion differentiation. As part of our sensitivity analyses, we repeated testing all hypotheses and research questions with positive emotion differentiation and two subcomponents of emotion regulation variability. These sensitivity analyses served to enrich our understanding on these understudied specifications (positive emotion differentiation and emotion regulation variability subcomponents). We tested all these hypotheses using data from five ESM studies, in which adolescents rated momentary emotions and emotion regulation strategies multiple times per day.

METHODS

This paper follows the Workflow for Open Reproducible Code in Science (Van Lissa et al., 2021). The pre-registration (hypotheses and analysis plan), data and analysis codes of this study are available via https://osf.io/cq6n4/?view_only=d0317604686d4ea6b65176672a722a64. In Supplemental Materials 1, we detailed our *a priori* power analysis which showed we had more than 80% power to test our confirmatory hypotheses and exploratory research question 1, and reported four minor deviations we had from our pre-registration.

Participants and Procedures

This study combines five ESM datasets (see Supplemental Materials 2 for details on participants and procedures). Table 3.1 shows an overview of the demographics per dataset. The five datasets included participants with a mean age of 17.4 years (*SD* = 3.0 ; range: 11 to 25 years), with 59.2% females (range across datasets: 47.7% to 77.6%). All studies, approved by respective ethical committees, were conducted in Belgium and the Netherlands with Dutch-speaking participants. All studies assessed participants either 10 times for 7 days or 5 times for 14 days, resulting in the same 70 observations. As pre-registered, we excluded 33 participants with zero variance in positive emotions, negative emotions or emotion regulation strategies. We further excluded 4 participants with an average reaction time below 500ms because it may indicate careless responding (K. O. McCabe et al., 2012). Participants completed on average 74% of all possible observations (*SD* = 23%). Supplemental Materials 2 has further details on participants and procedures of all datasets.

Table 3.1

Overview of Study Characteristics of Included Datasets

	G(F)ood together (Verhagen et al., 2022)	Emotions in daily life 2011 (Koval et al., 2013)	3-wave longitudinal study (Erbas et al., 2018)	Emotions in daily life (van Roekel & Trompetter, 2023)	Outside-in (Braet et al., 2023)
Institute	Radboud University, the Netherlands	KU Leuven, Belgium	KU Leuven, Belgium	Tilburg University, the Netherlands	Ghent University, Belgium
N after exclusion criteria applied	83	97	202	178	218
Age M (SD), range	16.4 (0.7), 15.0–18.0	19.1 (1.3), 18.0–24.0	18.3 (1.0), 17.0–24.0	20.9 (1.7), 18.0–25.0	13.5 (0.6), 11.0–15.0
Female	57%	63%	55%	78%	48%
Observations per day	10	10	10	5	5
Number of days	7	7	7	14	14
Interval scheme	Semi-random	Stratified-random	Stratified-random	Quasi-random	Fixed
Positive emotions	4 items: Content Relaxed Joyful Energetic	2 items: Relaxed Happy	3 items: Happy Relaxed Cheerful	7 items: Enthusiastic Content Energetic Calm Determined Cheerful Grateful	3 items: Happy Calm Enthusiastic
Negative emotions	5 items: Irritated Worried Depressed Insecure Lonely	4 items: Angry Anxious Depressed Sad	6 items: Angry Anxious Depressed Sad Lonely Stress	6 items: Angry Irritated Depressed Sad Nervous Bored	6 items: Angry Insecure Afraid Sad Stressed Bored
Emotion regulation strategies	5 items: Rumination Reappraisal Suppression Acceptance Social Sharing	6 items: Rumination Reappraisal Distraction Reflection Suppression Social Sharing	6 items: Rumination Reappraisal Distraction Worry Suppression Social Sharing	7 items: Rumination Distraction Avoidance Problem Solving Acceptance Co-Brooding Social Sharing	8 items: Rumination Reappraisal Distraction Self-Compassion (Support) Self-compassion (Cheer-up) Expression Suppression Social Sharing

Measures

ESM Measures

The studies differed in how many items were used to assess negative emotions, positive emotions, and emotion regulation strategies, but they all used multiple items with unipolar scales (see Table 3.1). Within each dataset, all items were rescaled before analyses to a scale of 0 to 10 to facilitate pooling across studies. Within-person correlations of items in the same scales were all lower than .80 (Supplemental Materials 3), indicating no multicollinearity problem (Katz, 2006; X. Wang et al., 2024). Intraclass correlation coefficients (ICC) of all items ranged from .19 to .64, indicating they had adequate within-person variance for further analyses. Supplemental Materials 2 has full item wordings for all items and the steps we have taken to assess their reliability and validity.

Momentary Indices Calculated from ESM Measures

Intensity of Positive Emotions, Negative Emotions, and Emotion Regulation. We calculated momentary intensities of negative emotions, positive emotions, and emotion regulation as the mean intensities of relevant items (e.g., in dataset 2, momentary negative emotion intensity is the mean of *angry*, *sad*, *anxious*, and *depressed*). Multi-level confirmatory factor analyses using the *lavaan* package (Rosseel, 2012) showed positive and negative emotions loaded separately on two factors as indicated with satisfactory fit indices (Supplemental Materials 4). Reliability was satisfactory for all indices within adolescents (positive emotion intensity: .60 to .80; negative emotion intensity: .66 to .76; emotion regulation intensity: .52 to .72) and between adolescents (positive emotion intensity: .88 to .93; negative emotion intensity: .90 to .94; emotion regulation intensity: .68 to .97).

Emotion Differentiation. To assess the degree of positive and negative emotion differentiation within adolescents at a specific moment, we calculated the momentary emotion differentiation index from the positive and negative emotion items (Erbas et al., 2021). This index was mathematically derived from the average consistency variant of ICC, a between-person measure of emotion differentiation commonly used in prior research to assess emotion differentiation. This index has no lower bound and an upper bound of 0 and it shows good predictive validity (Erbas et al., 2021). The momentary emotion differentiation index measures how consistently intensities of emotions are deviating in the same direction (i.e., positively or negatively) with regard to a person's mean. For example, if an adolescent has a mean rating of 3 in each of the four emotions assessed 70 times, a moment when all four emotions are rated at 5 will give a low value of momentary emotion differentiation, whereas a moment when two of the four emotions are rated higher (e.g., 6 and 5) and two lower (e.g., 0 and 1) will give a high value of momentary emotion differentiation (Figure 3.1).

Emotion Regulation Variability. We calculated momentary emotion regulation variability as Bray-Curtis dissimilarity from the emotion regulation strategy items. This index has recently been validated (Lo et al., 2024). This momentary index can be partitioned into two subcomponents that respectively detect two qualitatively different and theoretically relevant subcomponents (Aldao et al., 2015): endorsement change (e.g., from not using any strategies to using distraction) and strategy switching (e.g., replacing distraction with reappraisal). Bray-Curtis dissimilarity was calculated by comparing the moment of interest with all other moments the same adolescent reported (Figure 3.2) using the *betapart* package (Baselga et al., 2022; see Github tutorial at Lo, 2023). In this way, Bray-Curtis dissimilarity reflects the within-person deviation from their typical emotion regulation style - in terms of intensity or strategy selection[2]. Before calculating Bray-Curtis dissimilarity, we linearly transformed all emotion regulation intensity ratings by adding a small constant 0.001 to prevent division-by-zero computational errors, so that two moments with all strategies rated 0 can still be compared. Bray-Curtis dissimilarity index falls between 0 and 1. To improve comparison with other indices, we multiplied the Bray-Curtis dissimilarity index with 10 so it ranges from 0 to 10, where 0 indicates no variability and 10 represents the maximum variability possible, based on the emotion regulation intensity it is derived from.

Analysis

We conducted all analyses in this paper in R (R Core Team, 2023). After preparing each dataset, data were pooled into an overall dataset for analysis. To distinguish temporal effects (Hypothesis 1, 2, and exploratory research questions) from individual differences (Hypothesis 3), we separated observations of indices (emotion intensity, emotion differentiation, emotion regulation intensity, emotion regulation variability) into two components. The within-person component, which can vary at each time point, is the raw score minus the person-mean. The within-person component, which indicate an adolescent's time-invariant difference from others, is the person-mean minus the grand-mean (Bolger & Laurenceau, 2013).

Main Analyses

Pre-Registered Hypotheses. To test our hypotheses, we ran multilevel models. In model 1A, which corresponded to Hypothesis 1, emotion differentiation was the predictor and emotion regulation variability was the outcome. In model 2A, which corresponded with Hypothesis 2, emotion regulation variability was the predictor and emotion differentiation was the outcome. In the two multilevel models, observations (Level 1) were nested within participants (Level 2). Participants (Level 2) were further nested within datasets (Level 3) to account for between-dataset differences (see Boedhoe et al., 2019 for related

2 Another method to compute Bray-Curtis dissimilarity is by contrasting each moment with the preceding one. We ran sensitivity analyses with this successive temporal comparison approach. Results were generally consistent with what we present in the main text. Details can be found in Supplemental Materials 6.

methodological discussion). The outcome variables at each moment were predicted by the within-person components at Level 1 and between-person components at Level 2. We added negative emotion intensity and momentary emotion regulation intensity as covariates, because we wanted to examine the relations between predictor and outcome variables above and beyond mean intensities (Dejonckheere et al., 2019; O'Toole et al., 2021). Following a common practice analyzing ESM data, emotion regulation variability between two observations overnight were excluded (e.g., Siepe et al., 2025). We added time as a covariate, centered with the 35.5th observation as zero (midpoint of 70 observations), to control for any systematic time trends in the data. Age and gender were also added as time-invariant covariates. Time-varying within-person components of the predictor and control variables were entered both as fixed and random effects. Random intercepts and slopes were allowed to covary. Within-person components and centered time were entered as fixed effects. We included a first-order autocorrelation structure on the residuals. We used the *nlme* package (Pinheiro et al., 2022) to estimate multilevel models with the quasi-Newton optimizer.

In Hypotheses 1 (emotion differentiation predicting subsequent emotion regulation variability) and 2 (emotion regulation variability not predicting subsequent emotion differentiation) we were primarily interested in the fixed effects of the within-person components of the predictor variables in models 1A and 2A. For Hypothesis 1, we examined if the fixed effect differed significantly from zero. For Hypothesis 2, we used the two one-sided test approach to equivalence testing (Lakens et al., 2020) by inspecting whether the 90% confidence interval of the fixed effect crossed -0.187 and 0.187, the reference fixed slope we obtained in our power analysis (Supplemental Materials 1). To test Hypothesis 3 (adolescents with high emotion differentiation show high emotion regulation variability), we examined the significance of the fixed effect of between-person components in model 2A[3].

Exploratory Research Questions. We ran within-person mediation models to investigate the impact from emotion differentiation (predictor) to subsequent emotion intensity (outcome) via emotion regulation variability (mediator) with the R packages *nlme* and *lme4* (Bates et al., 2015). We restructured the data by stacking, which refers to splitting each row of data into two rows where one emphasizes the outcome (emotion intensity) and the other the mediator (emotion regulation variability) (Bauer et al., 2006; Bolger & Laurenceau, 2013). By doing so, the mediation model, inherently multivariate, can be fitted in the R packages we used, which only supported univariate modeling (McNeish & MacKinnon, 2022). After restructuring the data, we estimated the within-person mediation model, model 1M, which can be understood as an extension of Model 1A.

3 Model 2A was selected over model 1A for testing to allow easier comparison of estimates with our exploratory findings from model 2B. For sensitivity analyses, we selected model 2B to simultaneously assess both subcomponents on one side as predictors, unlike models 1B and 1C which split them as outcomes and predictors.

In model 1M, the predictor-outcome ("c'-path" from lagged differentiation to intensity) and the mediator-outcome ("b-path" from regulation variability to intensity) temporal relations were estimated simultaneously with the predictor-mediator temporal relation ("a-path" from lagged differentiation to regulation variability, originally included in Model 1A). Mediation effect is given by the sum of two components: the product of the predictor-mediator and mediator-outcome temporal relations ("a-path" and "b-path"), and the covariance of the two paths. The covariance term was included to account for how much the two paths co-vary within the same adolescents, informing the extent to which the mediation operates at the within-person level (Bolger & Laurenceau, 2013). To estimate the confidence interval of the mediation effect, we used the Monte Carlo method (Preacher & Selig, 2010), which required us to extract the following estimates of the predictor-mediator and mediator-outcome relations in model 1M: Fixed effect, residual variance, covariance of fixed effect, covariance of random effect, and asymptotic covariance of random effects. Other details regarding the specification of model 1M and testing the within-person mediation can be found in Supplemental Materials 5.

To test for pro-/contra-hedonic changes of emotion intensity for exploratory research question 1, we examined if the relevant fixed effects in the within-person mediation model differed significantly from zero. To test for mediation effect for exploratory research question 2, we inspected whether the 95% confidence interval of the mediation effect contained zero.

Sensitivity Analyses

Different Specifications of Momentary Indices. We ran models 1B, 1C, and 2B to explore the two subcomponents of emotion regulation variability. Model 1B and 1C followed the structure of model 1A, treating emotion differentiation as the predictor, but differed as follows: Model 1B made strategy switching the outcome and added endorsement change as a covariate; model 1C made endorsement change the outcome and added strategy switching as a covariate. Model 2B followed the structure of model 2A, treating emotion differentiation as the outcome but used both emotion regulation variability subcomponents (strategy switching and endorsement change) as simultaneous predictors in replacement of the full index in model 2A. We repeated all the analyses (model 1A, 1B, 1C, 1M, 2A, and 2B) by substituting negative emotion indices (differentiation and intensity) with positive emotion indices.

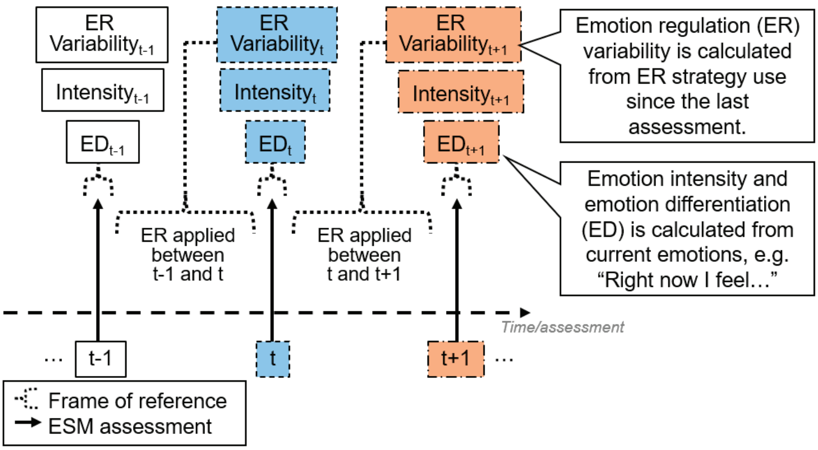
Robustness Across Adolescents' Age and Upon Measurement Occasions With Zero Negative Emotion (Regulation) Intensity. We also conducted a series of sensitivity analyses to investigate the robustness of the results of all models. These analyses included using an alternative temporal comparison operationalization of Bray-Curtis dissimilarity (Supplemental Materials 6), adding within-person moderators that tested the potential influence of within-dataset age differences (Supplemental Materials 7), and adding within-person moderators that tested the potential influence of zero negative emotion (regulation) intensity (Supplemental Materials 7). In the analyses with additional moderators, we considered our results robust if the main effects (i.e., the portion of effect without age or zero intensity as moderators) of the independent variables remain similar to the results from our main analyses.

Frame of Reference

In all datasets, the frame of reference for rating emotion regulation strategies was about regulating the negative emotions between the previous and current assessment (e.g., "Since the last beep, to change my negative feelings, I have sought for distraction"), whereas emotion items were assessed in terms of "right now" during each assessment (Figure 3.3). Therefore, associations between momentary emotion regulation variability and the emotion differentiation index, as derived from the same assessments, indicate that emotion regulation variability precedes emotion differentiation. As such, to examine Hypothesis 1 (heightened emotion differentiation is followed by subsequent increases in emotion regulation variability; model 1A to 1C), we used the lagged momentary emotion differentiation index as the predictor (and lagged momentary negative emotion intensity as covariate), and momentary emotion regulation variability as the outcome. In contrast, to examine Hypothesis 2 (emotion regulation variability does not affect subsequent emotion differentiation; model 2A and 2B), momentary emotion regulation variability as the predictor and the momentary emotion differentiation index as the outcome both came from the same assessment. Given the temporal sequence of lagged emotion differentiation, regulation variability, and emotion intensity observed in this frame of reference, we extended Model 1A to develop and run the within-person mediation model (Model 1M).

Figure 3.3

Frame of Reference



Note. t refers to the moment of interest. Tiles with similar colours and borders belong to the same moment.

RESULTS

Descriptive Statistics

On average, adolescents showed relatively low intensity of negative emotions and emotion regulation but moderate positive emotion intensity (Table 3.2). With regards to emotion differentiation and emotion regulation variability indices, within-person and between-person variance indicated that there is sufficient variation across time and between people. In Supplemental Materials 3, we detailed how we inspected the indices' distributions, assessed potential floor and ceiling effects, and compared correlations of momentary indices against published studies. In general, we considered it appropriate to further analyze emotion intensity, emotion differentiation and emotion regulation variability indices as the primary (in)dependent variables in our hypotheses.

Table 3.2

Descriptive Statistics of Momentary Indices of the Pooled Dataset (N=778)

Momentary index	Minimum Possible Value	Maximum Possible Value	Mean	Between-person SD	Within-person SD	Within-person Minimum	Within-person Maximum
Positive emotion intensity	0	10	5.78	1.65	1.53	2.16	8.54
Positive emotion differentiation	-Infinity	0	-1.98	0.76	3.06	-15.25	-0.03
Negative emotion intensity	0	10	1.46	1.16	0.98	0.3	4.57
Negative emotion differentiation	-Infinity	0	-2.15	0.82	4.8	-28.26	-0.03
Emotion regulation intensity	0	10	2.28	1.62	1.06	0.78	5.08
Emotion regulation variability (full index)	0	10	4.03	1.78	1.13	3.04	7.29
Endorsement change subcomponent	0	10	2.35	1.47	1.13	1.5	6.12
Strategy switching subcomponent	0	10	1.68	1.05	0.75	0.38	3.65

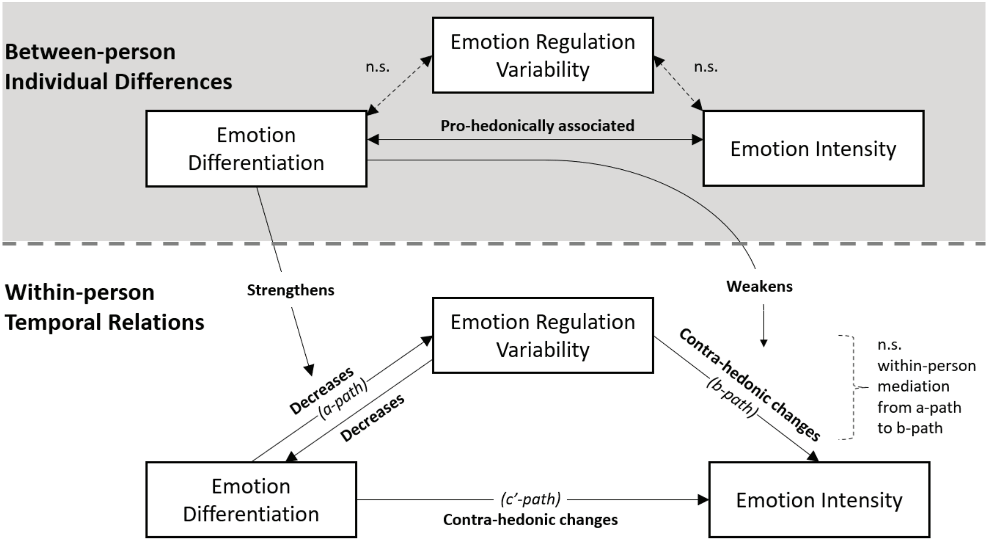
Main Analyses

Pre-Registered Hypotheses

In contrast with Hypothesis 1 (heightened emotion differentiation is followed by subsequent increases in emotion regulation variability within adolescents), model 1A (Table 3.3, Figure 3.4) results showed negative within-person associations between negative emotion differentiation and subsequent emotion regulation variability. This indicated that higher negative emotion differentiation at one moment was related to lower emotion regulation variability within adolescents at the subsequent moment. In contrast with Hypothesis 2 (emotion regulation variability does not affect subsequent emotion differentiation within adolescents), model 2A results indicated that higher emotion regulation variability at one moment was significantly associated with decreases in negative emotion differentiation at the subsequent moment[4]. In contrast with Hypothesis 3 (adolescents with high emotion differentiation show high emotion regulation variability), confirmatory analyses revealed no between-person association between negative emotion differentiation and emotion regulation variability (Model 2A, Table 3.3). This suggested that adolescents' average levels of negative emotion differentiation and regulation variability were unrelated. However, higher baseline negative emotion differentiation was pro-hedonically associated with lower average negative emotion intensity.

Figure 3.4

Summary of between-person individual differences and within-person temporal relations between emotion differentiation, emotion regulation variability, and emotion intensity.



Note. Pro-(contra-)hedonic refers to increased (decreased) positive emotion and decreased (increased) negative emotion intensity. n.s.: non-significant.

Exploratory Research Questions

Research question 1 explores changes in negative emotion intensity subsequent to fluctuations in negative emotion differentiation and emotion regulation variability. Model 1M suggested that both negative emotion differentiation and emotion regulation variability predicted an increase in subsequent negative emotions, bringing contra-hedonic changes. Research question 2 explores within-person mediation effect from negative emotion

4 Technically, the fixed effect tested in Model 2A crossed the reference slope at -0.187, meaning the equivalence proposed in Hypothesis 2 could not be confirmed. Additionally, the 95% confidence interval of the fixed effect did not include 0, indicating non-equivalence and suggesting that heightened emotion regulation variability was significantly associated with subsequent decreases in emotion differentiation.

differentiation to emotion intensity via emotion regulation variability. The temporal relations between the predictor and mediator ("a-path" from lagged differentiation to regulation variability) and the mediator and outcome ("b-path" from regulation variability to intensity) were both significant on average across all adolescents. However, there was no evidence on mediation effect, as the 95% confidence intervals for the indirect effect included zero. This suggests that the two temporal paths covaried in a manner that offset the potential mediation effect. Specifically, adolescents with a stronger a-path tended to have a weaker b-path, and vice versa, resulting in no overall within-person mediation. This covariance between the a-path and b-path can be characterized as co-moderation, meaning that both paths were simultaneously moderated. A further exploratory analysis showed that between-person negative emotion differentiation could be such a co-moderator: Higher baseline negative emotion differentiation intensified the negative a-path (moderated *b* = -0.005 [-0.009, -0.002]) and weakened the positive b-path (moderated *b* = -0.034 [-0.057, -0.011]) in Model 1M.

Table 3.3

Fixed Effect Estimates in Within-person Temporal Associations and Between-person Differences Between Emotion Differentiation and Emotion Regulation Variability

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***	**Model**
Within-person temporal hypotheses			
H1: Higher emotion differentiation is associated with subsequently higher emotion regulation variability (N = 751, n = 25851)			
Emotion differentiation → Emotion regulation variability	**-0.009 [-0.014, -0.005]**	**-0.009 [-0.014, -0.004]**	1A
Emotion differentiation → Strategy switching	**-0.004 [-0.007, -0.002]**	**-0.004 [-0.007, -0.000]**	1B
Emotion differentiation → Endorsement change	**-0.008 [-0.012, -0.004]**	**-0.007 [-0.012, -0.003]**	1C
H2: Emotion regulation variability is not associated with subsequent changes in emotion differentiation (N = 750, n = 25830)			
Emotion regulation variability → Emotion differentiation	**-0.514 [-0.731, -0.296]**	**-0.276 [-0.496, -0.057]**	2A
Strategy switching → Emotion differentiation	**-0.432 [-0.730, -0.133]**	**-0.306 [-0.525, -0.086]**	2B
Endorsement change → Emotion differentiation	**-0.550 [-0.771, -0.328]**	**-0.262 [-0.480, -0.043]**	2B
RQ: Emotion differentiation affects subsequent emotion intensity via emotion regulation variability (N = 755, n = 51991)			
a-path: Emotion differentiation → Emotion regulation variability	**-0.013 [-0.018, -0.008]**	**-0.014 [-0.020, -0.008]**	1M
b-path: Emotion regulation variability → Emotion intensity	**0.073 [0.038, 0.108]**	**-0.049 [-0.091, -0.006]**	1M
c′-path: Emotion differentiation → Emotion intensity	**0.008 [0.003, 0.013]**	**-0.016 [-0.026, -0.006]**	1M

Table 3.3

Fixed Effect Estimates in Within-person Temporal Associations and Between-person Differences Between Emotion Differentiation and Emotion Regulation Variability (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***	**Model**
Mediation (sum of covariance and product of a- and b-path)	-0.000 [-0.001, 0.001]	-0.000 [-0.001, 0.001]	1M
Between-person hypothesis			
H3: Higher emotion differentiation is associated with higher emotion regulation variability (N= 750)			
Emotion differentiation←→Emotion regulation variability	-0.035 [-0.072, 0.001]	-0.012 [-0.039, 0.015]	2A
Emotion differentiation←→Strategy switching	0.055 [-0.008, 0.118]	-0.004 [-0.052, 0.044]	2B
Emotion differentiation←→Endorsement change	**-0.091 [-0.140, -0.042]**	-0.018 [-0.055, 0.019]	2B
Other exploratory analyses (N= 750)			
Emotion intensity←→Emotion differentiation	**-0.238 [-0.296, -0.180]**	**0.035 [0.005, 0.065]**	2A
Emotion intensity←→Emotion regulation variability	-0.023 [-0.128, 0.083]	**-0.107 [-0.181, -0.034]**	1A
Emotion intensity←→Strategy switching	0.032 [-0.022, 0.085]	-0.035 [-0.073, 0.002]	1B
Emotion intensity←→Endorsement change	-0.072 [-0.148, 0.004]	0.025 [-0.028, 0.079]	1C

Note: Significant effects are displayed in bold. →: temporal precedence; ←→: between-person association; n: number of ESM assessments with complete observations of all indices required for modeling; N: number of adolescents; b: unstandardized effect; CI: confidence interval; H1 – H3: Hypotheses 1 to 3. RQ: Exploratory research questions. Negative emotions and positive emotions were analyzed in separate models. Small differences in n and N between models exist due to different availability of indices as required in the different models. For brevity, we displayed the smaller n and N of the models grouped under the same hypotheses. H1 was tested using three negative emotion models and three positive emotion models because of three outcome variables (emotion regulation variability and its two subcomponents). H2 was tested using two models for positive emotions and two models for negative emotions. Two subcomponents were included together in model 2B. In Model 1M, n is doubled because of how data have undergone the stacking preparation step. Full model results with estimates of covariates (emotion intensity, emotion regulation intensity, time, gender, and age) are available in Supplemental Materials 5.

Sensitivity Analyses

All three hypotheses and exploratory research questions were generally robust against sensitivity analyses: They held for both positive and negative emotion intensity and differentiation, for both subcomponents of emotion regulation variability (Table 3.3 and Supplemental Materials 5), alternative specification of Bray-Curtis dissimilarity (Supplemental Materials 6), or when moderation effects of age and zero emotion (regulation) intensity on the hypothesized within-person relations were controlled for (Supplemental Materials 7 and 8). In other words, emotion differentiation - whether positive or negative - and emotion regulation variability, regardless of the specific subcomponent, seemed to hinder each other subsequently. Additionally, emotion differentiation and emotion regulation variability both introduce subsequent contra-hedonic changes, in terms of increased negative emotion and decreased positive emotion intensity. However, in terms of individual differences, adolescents with higher emotion differentiation tended to have more pro-hedonic emotion intensity in general (higher positive emotion and lower negative emotion intensity). Evidence of robustness was the strongest for our pre-registered hypotheses specified with negative emotions. Exploratory research questions results were also generally robust, but with increasingly nuanced evidence for analyses with compounding exploratory specifications (e.g., positive emotions and moderation by age).

Across datasets, the within-person effects in our main analyses were consistent in direction, indicating that the results were driven collectively by all datasets rather than being influenced disproportionately by one or two (Supplemental Materials 8). Our within-person results appeared to be stronger among datasets that sampled late adolescents. However, in most models, dataset-centered age did not moderate the within-person relations.

DISCUSSION

Using five ESM datasets that encompassed 25,834 observations in 750 adolescents, we tested whether higher emotion differentiation was related to higher subsequent emotion regulation variability and changes in emotion intensity. Contrary to expectations, our pre-registered analyses showed that momentarily heightened differentiation of negative or positive emotions predicted lower subsequent emotion regulation variability, indicating greater stability in deploying regulation strategies. Reciprocally, increased deviation from typical emotion regulation strategies (i.e., higher variability) predicted less emotion differentiation at the next assessment. Exploratory analyses further showed that moments of heightened emotion differentiation and regulation variability were both followed by feeling worse, with increased negative and decreased positive emotion intensity. These effects were consistent across two subcomponents of regulation variability (endorsement change and strategy switching) and held true regardless of whether emotion differentiation involved positive or negative emotions.

Although our results did not reveal between-person associations between emotion differentiation and emotion regulation variability, individual differences in emotion differentiation might have moderated within-person processes. Specifically, the higher baseline negative emotion differentiation adolescents have, the more intensified negative reciprocal relations between negative emotion differentiation and emotion regulation variability are, but the more adolescents are buffered from contra-hedonic changes in negative emotion that follow momentarily higher emotion regulation variability.

In summary, our results add to the theoretical understanding of how emotion differentiation may influence emotion regulation. At both within-person and between-person levels, emotion differentiation influences subsequent within-person fluctuations in emotion regulation strategy use and emotion intensity.

Possible Explanations of the Interplay between Emotion Differentiation, Emotion Regulation Variability, and Emotion Intensity

A possible explanation for the negative reciprocal relationship between emotion differentiation and emotion regulation variability is that these processes may compete for the same mental resources; when one is more active, the other may consequently decline. Mental effort could represent such a cost. Emotion differentiation has been theorized as an effortful process in daily life (Erbas et al., 2019; Wranik et al., 2007)and shown to be so in experimental settings requiring participants to label emotions (Lieberman & others, 2011; Torre & Lieberman, 2018). Additionally, a recent review indicated that emotion regulation demands effort and can lead to fatigue (Lewczuk et al., 2022). Given that both processes require effort, high emotion differentiation may restrict variability in emotion regulation strategies, and vice versa. This "effort as cost" perspective may also explain changes in negative emotion intensity. A recent meta-analysis synthesizing 170 studies revealed that mental effort strongly correlates with higher negative emotion intensity across various tasks and populations, including late adolescents aged 18 to 25 (David et al., 2024). Consistent with this finding, experiments have demonstrated that labeling emotions in addition to initiating a regulation strategy counteracts the strategy's prohedonic effects in responding to aversive stimuli (Nook, Satpute, et al., 2021). Thus, our findings that negative emotion intensity increased following emotion differentiation and emotion regulation variability may result from—or reflect—the exertion of mental effort.

Contra-hedonic changes in emotion intensity may also be explained by the assumption that there is an increase in attention to emotion following increased emotion differentiation (Thompson et al., 2011). However, this intensifying mechanism explains only the increase in negative emotion intensity, not the decrease in positive emotion intensity. One possible explanation lies in the differing tendency of attending to positive versus negative emotions. Individuals, including late adolescents aged 18 to 25, typically avoid negative emotions and embrace positive ones; studies indicate a tendency to approach positive-valence stimuli and avoid negative ones (Krieglmeyer et al., 2010; Phaf et al., 2014) by resisting attention to aversive experiences (D. S. Lee et al., 2024). Hence, it is possible that to heighten emotion differentiation, individuals must pay extra attention to negative emotions, but not necessarily so to positive emotions, because they already do. This could lead to a "double increase" in negative emotion intensity, both due to the greater attention and exertion of effort. In contrast, positive emotion intensity may decrease because the effortful nature of differentiation likely outweighs the minimal intensifying effects on positive emotions due to little attentional increase.

Baseline Negative Emotion Differentiation May Co-moderate the Two-Step Within-Person Processes

Our within-person results on the temporal sequence—from emotion differentiation to regulation variability, and from regulation variability to intensity change—appear to suggest that differentiated emotions help adolescents' emotion regulation by fostering consistent use of strategies (resulting in low variability) that lead to pro-hedonic emotion intensity outcomes. However, the within-person mediation analyses do not support this two-step pathway. Instead, our results highlight individual differences in these sequential processes by how they have been co-moderated. This co-moderation effect reveals that adolescents who display a stronger connection in one of these relations tend to show a weaker connection in the other. Our results suggest that baseline emotion differentiation at the person level may act as a co-moderator. Specifically, high baseline negative emotion differentiation intensifies the negative temporal relation from negative emotion differentiation to emotion regulation variability, while buffering adolescents from contra-hedonic outcomes following increased regulation variability. As a result, within-person changes in emotion intensity arise directly from differentiation itself, rather than being mediated through regulation variability.

Are Momentary Contra-Hedonic Emotion Intensity Changes at Odds With the Long Term Benefits of Emotion Differentiation?

Our results show that adolescents with higher baseline emotion differentiation are more likely to have higher levels of positive emotions and lower levels of negative emotions in general (Table 3.3, Supplemental Materials 3). These are in line with earlier reports describing that individuals with higher baseline emotion differentiation tend to experience better well-being (Seah & Coifman, 2024). Cross-sectional data have suggested that adolescents may experience a dip in their emotion differentiation before developing to higher levels as they age (Nook et al., 2018). A promising direction for future research would be to examine whether repeated momentary efforts to increase emotion differentiation yield long-term benefits in improving baseline emotion differentiation and well-being. While short-term contra-hedonic outcomes may seem like an obstacle for voluntarily heightening momentary emotion differentiation, adolescents may be well-suited for this challenge: Compared to older adults, adolescents are more inclined to tolerate contra-hedonic experiences if such experiences contribute to long-term goals (Riediger et al., 2009; Tamir, 2009).

Open Developmental and Contextual Questions in Emotion Differentiation and Emotion Regulation Variability

Due to differing study designs across datasets and lacking contextual data, it was not feasible for us to formally test age differences or contextual influence.

Future research should explore the development of emotion differentiation and emotion regulation variability across adolescence, ideally using a single large dataset encompassing the entire adolescent age range. Drawing on prior work that suggested nonlinear development in emotion differentiation (Nook et al., 2018), researchers may investigate whether emotion regulation variability also follows a nonlinear trajectory during adolescence. This could be due to adolescents' intermediate experimentation with an expanding repertoire of regulation strategies (Elkjær et al., 2022). Middle adolescence, in particular, may feature heightened variability, as adolescents in this stage are less likely to regulate emotions like sadness and anger compared to younger or older peers (Zimmermann & Iwanski, 2014). These middle adolescents may have more frequent all-or-nothing changes in employing emotion regulation strategies, leading to greater observed variability.

Future research should investigate how emotion regulation variability relates with contexts. Our exploratory findings indicated that increased emotion regulation variability preceded contra-hedonic changes in emotion intensity, a result contrasting with Lo et al. (2024)'s initial findings, which suggested that this variability reduces subsequent negative emotion intensity (but did not control for covariates such as prior emotion regulation intensity). Additionally, the contra-hedonic effect of heightened emotion regulation variability was moderated by person-level emotion differentiation. This aligns with recent literature showing that other conditions, such as emotion regulation goals and contexts, significantly shape emotion regulation variability (Liao et al., 2024). Furthermore, it has been proposed that emotion regulation variability attuned to shifting contexts or that emerged when prior strategies are ineffective differs conceptually from variability that is context-insensitive (Kalokerinos & Koval, 2024; Southward et al., 2018). Interpreting emotion regulation variability in relation to changes in contexts and goals enables researchers to ask under what contexts high or low variability benefits adolescents. These questions could enhance our understanding of the dynamics between context and strategy use, which is increasingly seen as central to defining adaptive emotion regulation in daily life (Aldao et al., 2015; Paul et al., 2023).

Limitations

Other limitations must be considered when interpreting our results. First, there is heterogeneity across datasets due to varying sample characteristics and ESM protocols. We have included dataset-level random intercepts to mitigate this, but future studies should explore how these study characteristics affect outcomes. Second, the generalizability of our conclusions depends on the scope of emotions and emotion regulation items included. Caution must be applied in generalizing sensitivity analysis results on positive emotions due to having few items in some datasets for forming positive emotion momentary indices. In contrast, our confirmatory results about negative emotion differentiation are more generalizable because of being derived from at least four negative emotion items. Although our datasets selected conventional items from emotion (regulation) theories (Supplemental Materials 2), they did not cover maladaptive behaviours such as non-suicidal self-injury (L. F. Zaki et al., 2013) and alcohol consumption (Kashdan et al., 2010), which have been linked to poorer negative emotion differentiation. These behaviours can be treated as emotion regulation strategies in an expanded framework of emotion regulation (Seah & Coifman, 2021). Therefore, future studies may reexamine our results by widening the scope of emotions and emotion regulation items. Researchers may additionally consider the use of personalized items (e.g., Olthof et al., 2023), given the idiographic nature of emotion and emotion regulation (Entwistle et al., 2023; Grommisch et al., 2020). Third, in our analysis, we assumed equal intervals in the temporal sequences of emotion differentiation and emotion regulation variability, but in reality, they varied due to study designs (Table 3.1) and the frame of reference (Figure 3.3). Future research should consider methodologies that can model irregular time intervals (e.g., Asparouhov & Muthén, 2020) to validate our findings.

Practical Implications

Our study provides three considerations for practitioners in emotion-focused psycho-education (e.g., Metz et al., 2013). First, training emotion differentiation and regulation variability separately may be more effective than a combined one-session approach. Our within-person findings suggest these processes can hinder each other, and combining them may be counterproductive. Second, practitioners should anticipate short-term discomfort following increased emotion differentiation or regulation variability. To support participants, they might consider complementing training with techniques to hasten recovery from worsened feelings and emphasize the long-term benefits to maintain motivation. Third, pre-training assessments of adolescents' baseline emotion differentiation could be valuable. Our between-person findings suggest that adolescents vary in training needs; for instance, those with higher baseline differentiation may show a stronger negative relationship from differentiation to regulation variability, while others may experience a stronger positive link from regulation variability to contra-hedonic outcomes. However, it is important to note that our findings are correlational and do not predict how these processes may interact post-intervention.

Conclusion

To conclude, this well-powered study is the first to test how emotion differentiation temporally influences emotion regulation variability and emotion intensity in adolescents' daily lives. Our findings suggest that, at least in the short term, emotion differentiation and emotion regulation variability hinder each other, regardless of the type of variability (endorsement change or strategy switching) or valence of emotions (positive or negative). Furthermore, contra-hedonic emotional intensity changes follow momentarily heightened emotion differentiation or regulation variability. Adolescents differ in these within-person processes. Specifically, high baseline emotion differentiation intensifies the negative reciprocal relationship between differentiation and regulation variability, while buffering them from contra-hedonic outcomes following increased regulation variability. These results prompt reconsideration of how emotion differentiation supports emotion regulation, highlighting within-person processes that may enable practitioners to better tailor emotion-focused mental health interventions for adolescents.

4

Negative Emotion Transitions Are Temporally Close to Reductions in Overall Negative Emotion Intensity in Daily Life

This chapter is based on a manuscript currently under peer-review.
Lo, T. T., Maciejewski, D. F., Vervoort, L., Vink, J. M., Cheng, T. N., Pouwels, J. L., & Verhagen, M. (2026). Negative Emotion Transitions May Have Immediate Benefits in Decreasing Negative Emotions in Daily Life. Preprint: https://doi.org/10.17605/OSF.IO/E6U97.

ABSTRACT

Transitioning from one negative emotion to another (e.g., from anger to sadness) is thought to reflect emotional flexibility. Observational studies have shown that negative emotion transitions are associated with short-term reductions in negative emotion intensity, with potentially greater benefits for individuals with higher depressive symptoms. However, it is unclear if these transition-intensity reduction associations also occur in daily life in young adults, who are prone to depressive symptoms. We analyzed three samples of young adults (N_{total} = 365, n = 17,587) who reported their negative emotions multiple times a day in experience sampling studies. Applying an ecology index, Bray-Curtis dissimilarity, we demonstrated that transitions between negative emotions were concurrently associated with reductions in their overall intensity within hourly intervals. Moreover, such associations were stronger among more depressed young adults. Findings suggest everyday negative emotion transitions may be clinically informative, particularly among young adults with elevated depressive symptoms.

Keywords: Depressive Symptoms, Dynamics, Experience Sampling Method, Emotion Transition, Negative Emotion

NEGATIVE EMOTION TRANSITIONS ARE TEMPORALLY CLOSE TO REDUCTIONS IN OVERALL NEGATIVE EMOTION INTENSITY IN DAILY LIFE

Emotions can change over time, not only in intensity but also in type. While it is easy to imagine a transition from negative to positive emotions (e.g., sadness to happiness), other situations can involve transitions from one negative emotion to another negative emotion. Imagine a young adult who receives an email informing him that he was not selected for a prestigious job after months of application process. Initially, he may feel angry toward the rejection. That anger may give way to sadness over losing a dream opportunity and what seems like wasted effort, before the negative emotional experience finally subsides.

Despite their relevance to everyday experience, little is known about negative emotion transitions in daily life. Here, we study how these transitions unfold in young adults' daily lives and how such transitions are associated with changes in overall negative emotion intensity. Specifically, we test whether transitions between negative emotions systematically accompany reductions in their experienced intensity within1.5-to-3-hour intervals. We refer to this hypothesized association as negative emotion transition–intensity reduction associations. This hypothesis is informed by theoretical and empirical work from affective science, dynamic systems, and psychotherapy research. From these perspectives, negative emotion transitions indicate emotional flexibility. Transitions between negative emotions may reflect flexibly updates of information and action tendencies signaled by emotions, with clarity and focus. This may in turn support responses that better address emotional needs and reduce negative emotional intensity (Frijda, 2016; Hollenstein et al., 2013; Schwarz & Clore, 1983; Singh et al., 2021). Given that adults with higher depressive symptoms exhibit larger reductions in negative emotions upon increases in positive emotions (Bylsma et al., 2011; Panaite et al., 2019), , and that the only study about negative emotion transition-intensity reduction associations was only conducted in depressed psychotherapy clients (Singh et al., 2021), we also examine whether levels of depressive symptoms moderate these associations. We focus on young adults for two reasons. First, compared to older adults, they tend to experience more frequent and intense negative emotions that demand regulation (Bailen et al., 2019; Zimmermann & Iwanski, 2014). Second, this age group is at significant risk of depressive symptoms (McGorry et al., 2024; Solmi et al., 2022).

Negative Emotion Transition: Multiple Negative Emotions, One at a Time

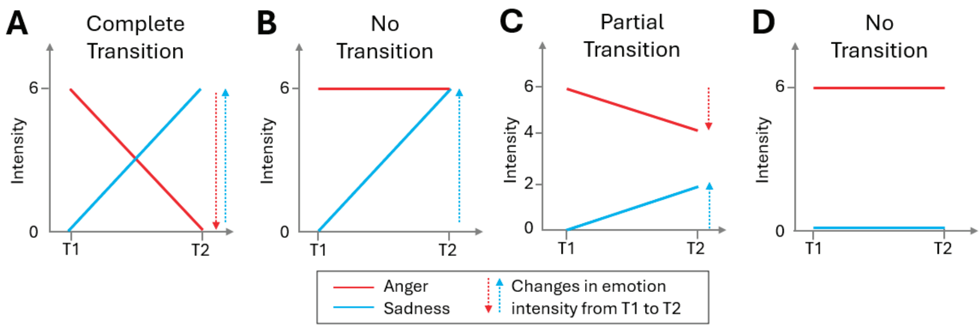
Emotions can be considered as collections of autonomic arousals and appraisals that prepare a person to take action to relate to the world (Frijda, 2016). Negative emotions, unpleasant as they may be, serve informative and functional purposes. Negative emotions are *informative* to individuals about the nature of the current situations, highlighting the unmet needs relevant to those situations (Greenberg, 2006; Schwarz & Clore, 1983). Thus, negative emotions are *functional* as they may make individuals action-ready by coordinating responses to meet emotion-specific needs (Frijda, 2016; Lench et al., 2015; Mauss et al., 2005; Weidman & Kross, 2021). Returning to the job application example, anger and sadness illustrate these informative and functional purposes. Anger signals a perceived threat to self-worth, reflecting a need for validation of one's abilities; anger may mobilize the young adult to act to reestablish his value. Sadness signals the loss of a job opportunity and the effort invested in preparation, indicating the young adult's needs for rest and comfort; sadness may demobilize further immediate action and coordinate bodily and facial expressions in ways that elicit support and encouragement from peers.

Multiple negative emotions, such as anger and sadness, can unfold with or without transitions. When emotions like anger and sadness take place one at a time —that is, with transitions—individuals have a clear understanding regarding the emotion-eliciting situations and develop distinct action readiness in response, addressing specific needs one at a time. Even when needs are judged unattainable, the updated appraisal of the situation is carried forward to elicit the next emotion (Brosch et al., 2013; Scherer, 2009). C Continuing with the job rejection example, in Figure 4.1A, anger may give way to sadness when further action (e.g., calling a recruiter) seems pointless, resulting in a complete transition (red line decreases and blue line increases; Figure 4.1A). In contrast, in Figure 4.1B, there is no transition as sadness rises (blue line increases) but anger does not fade (red line stays flat). In this case, action-readiness from different emotions can become incompatible, as feeling angry and sad simultaneously may create tension between taking action and withdrawal. As a result, the young adult may struggle to follow through with any one response, increasing the likelihood that his needs remain unmet (e.g., reestablishing self-worth as signaled by anger and solace signaled by sadness; Frijda, 2016). In daily life, emotion transitions are not necessarily all-or-none, but can occur to varying degrees. For example, in Figure 4.1C, anger (red line) decreases slightly and sadness (blue line) increases slightly, resulting in a partial transition. Naturally, absence of transitions can also happen when all emotions stay unchanged, like in Figure 4.1D where the two lines that represent anger and sadness stay flat.

Emotion transition is related to, but distinct from, emotion differentiation. Emotion differentiation refers to how distinctly an individual labels one's emotional experience (Barrett et al., 2001). Similar to emotion transition, emotion differentiation is theorized to benefit the individual with clarity in information and action-tendency signaled by emotions (Erbas et al., 2021). When several emotions are experienced at similar intensity, such moments are considered to reflect low emotion differentiation, as in T2 of Figure 4.1B, where anger and sadness are rated equally (Erbas et al., 2021); When one emotion is more prominent than the others, such moments are considered to reflect high emotion differentiation, as in all time points in Figures 4.1A and 4.1D. By contrast, emotion transitions describe a dynamic process and can occur independent of how differentiated emotions are within the moments that make up the transition. High differentiation on its own does not imply that a transition has occurred (cf. Figure 4.1A and 4.1D). As we will review below, changes in the type of negative emotions, uniquely indicated by emotion transitions, may be closely related to changes in overall negative emotion intensity.

Figure 4.1

Example Patterns of Complete, No, and Partial Negative Emotion Transitions (Panel A to D).



Note. Presence of transitions can be determined by compensatory changes as indicated by arrows with **opposing** directions. In Panel A and C, decreases in anger (red lines and downward arrows) are compensated by increases in sadness (blue lines and upward arrows), indicating presence of transitions. In Panel B, there is only an increase in sadness (blue line and upward arrow) without a compensatory decrease in anger (no red downward arrow), hence no transition. In Panel D, there are no changes (no arrows), indicating absence of transitions.

Dynamics Systems Perspective: Emotion Transitions Indicate Emotional Flexibility

From a dynamic systems perspective, negative emotion transitions reflect flexibility in a person's emotion system. Emotions can be viewed as a system because they are interconnected and predict each other over time (Hollenstein, 2015; Thelen et al., 1991). The emotion system is treated as a unit of analysis, so that its variability is not noise (e.g., measurement error) but a signal about the system's state and functioning. Just like how various species in an adaptive ecosystem fluctuate in their population sizes upon internal (e.g., diseases) and external (e.g., weather shifts) forces, variability of emotions reflect the system's response to internal cues, such as physiological arousal and cognitive appraisals, as well as external perturbations, such as a job rejection (Hollenstein et al., 2013; M. D. Lewis, 2005). Within a multiple-emotion system, changes can take the forms of intensity, where emotions get stronger or weaker, and type, where one emotion changes into another, i.e., emotion transitions (Gross & Jazaieri, 2014; Hollenstein et al., 2013). Without changes in intensity or type, a negative emotion is sustained. Even when that emotion is clearly differentiated, its sustained presence may indicate that the information and action tendency it signals are no longer helping the person respond effectively to the situation. Going back to the job rejection example, sustained anger and the urge to call the recruiter may do little to change the situation. Emotion transitions may therefore matter not only because they reflect greater clarity when there are multiple emotions, but also because they reflect flexible updates in the emotion system. In this way, a new emotion may bring new information and a different action tendency that is better suited to current demands.

Empirical support on the notion that emotion transitions may indicate flexibility comes from laboratory studies about parent–child conflict discussions, where trained observers coded participants' expressed emotions moment by moment into mutually exclusive emotion categories. In this context, emotion transitions are thought to reflect flexibly adapting to partners' emotions and making responses to renegotiate as the conflict discussions evolve (Branje, 2018). Children and adolescents who showed more emotion transitions in the hour of laboratory conflict discussion, which include transitions between negative emotions, tended to have a lower risk for later internalizing problems (Hollenstein et al., 2004; Van der Giessen et al., 2015).

Emotion transitions do not appear to only associate with long-term psychopathology outcomes, but also concern short-term changes in emotion intensity. This short-term link between emotion transitions and emotion intensity change has been found in daily-life and psychotherapy contexts in individuals with depressive symptoms.

Emotion Transitions Among Adults with Elevated Depressive Symptoms

In daily life, young and middle-aged adults with depression or elevated depressive symptoms had greater reductions in negative emotions in hourly intervals when they experienced increases in positive emotions brought by positive events or daily activities (Bylsma et al., 2011; Khazanov et al., 2019; Panaite et al., 2019; van Loo et al., 2023). In this pattern, which is often referred to as the mood brightening effect, emotion transitions are in play because positive emotion increases while negative emotion decreases.

The short-term reduction in negative emotion intensity in depressed individuals is consistent with the dynamic systems perspectives that flexibility within the emotion system can be beneficial. Depressive symptoms are characterized by emotional inflexibility, in that there is a sustained experience of a dominant negative emotion such as sadness (Garvey et al., 1989; Gross & Jazaieri, 2014; Holtzheimer & Mayberg, 2011; Kashdan & Rottenberg, 2010; Wen & Yoon, 2019). If young adults with depressive symptoms are capable of being emotionally flexible, they may experience a larger benefit from such flexibility than healthy young adults. Because dynamic systems perspectives view positive and negative emotions as part of the same broader emotion system, this benefit may not be limited to flexibility between negative and positive emotions. It may also extend to flexibility between negative emotions themselves. Supporting this idea, individuals high in depressive symptoms who show greater moment-to-moment variability in the intensity of negative emotions tend to report lower overall negative emotion intensity (Maciejewski et al., 2023). However, research in everyday emotions has not yet tested whether variability in the type of negative emotions, i.e., negative emotion transitions, is associated with reduction in the overall intensity of negative emotions.

Evidence from psychotherapy research supports this possibility. In psychotherapy, clients' emotion transitions are viewed as markers of emotional flexibility (Pascual-Leone, 2009). An emotion transition begins when clients experientially attend to their original, presenting emotion, respond to the needs it signals, and clarify the meaning it holds. This process reshapes clients' internal state and can give rise to a new emotion, completing an emotion transition (Auszra et al., 2013). The new emotion is often still negative, especially in early sessions, but it signals another unmet need to work on. Over time, as clients iterate through emotion transitions and address each underlying need, they are said to have processed their emotions. The result is a reduction of symptoms and negative emotion intensity. Within this framework, negative emotion transitions are not only common but essential, enabling clients to flexibly progress rather than remaining stuck in one negative emotion. This notion is supported by two studies that analyzed videotaped therapy sessions. Specifically, trained raters systematically categorized clients' expressed emotions during therapy moment by moment as one of the 11 emotional states defined in a validated coding system (Pascual-Leone, 2018; Pascual-Leone & Greenberg, 2005). Transitions were derived from changes from one coded emotion to another. The first study sampled clients with mood and/or interpersonal issues. Clients who displayed more negative emotion transitions were more likely to perceive their emotions as helpful and had shorter episodes of distress when such episodes reoccurred (Pascual-Leone, 2009). Another study focused on clinically depressed clients. Clients who had more negative emotion transitions in a psychotherapy session showed reductions in negative emotion intensity, as part of symptom reduction, right after the psychotherapy session (Singh et al., 2021)[1]. However, it remains unclear whether the same negative emotion transition-intensity reduction associations occur in daily life outside of the therapeutic context, and the moderating role of depressive symptoms in these associations has not been systematically examined.

1 Our study relies on self-reported emotions, which can diverge from externally observed emotions despite their high correlation (Mauss et al., 2005). In psychotherapy, moment-to-moment self-reports are rarely feasible, as clients are actively engaged with limited opportunities for ongoing self-assessment.

The Present Study

To address these gaps in the literature, the present study tested two hypotheses in young adults. Hypothesis 1 states that negative emotion transitions in daily life are associated with overall decreases in negative emotion intensity in the same hourly intervals. Given the empirical evidence from psychotherapy and mood-brightening studies that individuals with depressive symptoms benefit from emotion transitions, Hypothesis 2 states that negative emotion transition-intensity reduction associations are more pronounced in young adults with higher levels of depressive symptoms (i.e., greater decrease in intensity of negative emotions) than in young adults with lower depressive symptoms. In both hypotheses, we focus on concurrent associations within hourly intervals (between two experience sampling method [ESM] assessments). This is because the closest existing evidence, particularly from psychotherapy research, suggests that negative emotion transitions and intensity reduction can unfold over a comparable time frame within a single psychotherapy session. Although we intentionally used simplified two-emotion examples so far for better introducing the concept of emotion transition, our analyses examined transitions among the broader range of negative emotions typically assessed in ESM studies, as an initial step toward characterizing negative emotion transitions in daily life. To cross-validate findings, we analyzed three young adult samples with similar characteristics that reported on their everyday momentary negative emotions in ESM studies. As we will shortly introduce, two of the samples were recruited based on pre-screened levels of depressive symptoms, allowing us to more effectively test Hypothesis 2.

METHODS

Participants and Procedures

Table 4.1 shows an overview of the demographics of the three studies we analyzed. All studies recruited university students, but Dataset 2 and 3 used a stratified sampling approach (Ingram et al., 2009) to increase the individual differences in depressive symptoms, improving our ability to test whether depressive symptoms moderate the transition-intensity reduction association (Hypothesis 2). Specifically, 439 and 686 participants respectively completed pre-screenings in Dataset 2 and 3 with the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977) before the actual study and data collection. Then, participants were sorted by their CES-D pre-screening scores and assigned to five roughly equal-sized segments. Finally, a random sample of participants was recruited from each segment (Brans et al., 2013; Koval et al., 2015).

The recruited samples from the three datasets included 70, 95 and 202 participants ranging from 17 to 30 years old (*M*age = 19.9 years; *SD* = 1.57), with 56% females. The original authors determined the sample sizes based on their prior experience in conducting ESM studies (Dataset 1) and on statistical power for the expected effect sizes in Dataset 2 (correlations of approximately .30) and Dataset 3 (d = .30, assuming an attrition rate of 25%). All studies used the CES-D to measure depressive symptoms. Note that in Dataset 2 and 3, depressive symptoms were measured again after the pre screening phase. We excluded one participant in Dataset 2 and one participant in Dataset 3 because they gave the same responses across all CES-D items which contained reverse-coded items, indicating careless responding. Dataset 1, 2, and 3 respectively, had 43%, 24%, and 17% young adults who were potentially clinically depressed based on their CES-D scores (Vilagut et al., 2016)[2]. Participants also reported on their emotions using ESM for 6 to 10 times per day over 7 to 9 days, resulting in 54 to 70 possible observations per study. Participants completed on average 84.4% of all possible observations, which was higher than the 78% average compliance rate in many ESM studies as summarized in Rintala et al. (2019). The sample sizes and number of ESM observations in these datasets were not originally determined to address the current research question, . Supplemental Material 1 has further details on participants and procedures of all datasets.

2 Calculated using a cut-off score of 20 points on a scale of 60 in dataset 1 and 2 and 26.7 out of a scale of 80 in dataset 3. This cut-off score, more conservative than the cut-off in the original scale (16 points on a scale of 60, Radloff, 1977), showed a good sensitivity-specificity trade-off in indicating potential clinical depression (Vilagut et al., 2016),

Table 4.1

Overview of Dataset Characteristics

	Dataset 1 (Blanke et al., 2018)	**Dataset 2 (Koval et al., 2013)**	**Dataset 3 (Erbas et al., 2018)**
Institute	Humboldt-Universität zu Berlin, Germany	KU Leuven, Belgium	KU Leuven, Belgium
Year of data collection	2015	2011	2012
N (N after exclusion)	70 (70)	95 (94)	202 (201)
Age *M(SD)*, range	25.6 (2.8), 20-30	19.1 (1.3), 18-24	18.3 (1.0), 17-24
Female	50%	63%	55%
Racial Identification	Not available	European (92%) Others (8%)	African (1%) Asian (1%) European (96%) Middle-Eastern (1%)
Native language	German (97%)	Dutch (94%)	Dutch (94%)
ESM Observations per day	6	10	10
Number of days in ESM	9	7	7
ESM Interval scheme	Semi-random, about every 3 hours	Stratified-random, about every 1.5 hours	Stratified-random, about every 1.5 hours
ESM Negative emotion	Nervous Downhearted Distressed	Angry Anxious Depressed Sad	Angry Anxious Depressed Sad Lonely Stressed
Item stem	How have you primarily felt? Please rate how well the following emotion adjectives describe your feelings during this time period.	How [emotion] have you felt at the moment?	How [emotion] do you feel at the moment?
Answering scale	7-point scale from 0 (does not apply at all) to 6 (applies strongly)	Slider scale from 1 (not at all) to 100 (very much)	Slider scale from 0 (not at all) to 100 (very much)
Reference frame	Since waking up/since the last assessment	At the moment of the assessment	At the moment of the assessment
Depressive symptoms	20-item CES-D	20-item CES-D	20-item CES-D
Answering scale	5-point scale from 0 (never) to 4 (always)	4-point scale from 0 (rarely or none of the time, less than 1 day) to 3 (most or all of the time, 5-7 days)	4-point scale from 0 (rarely or none of the time, less than 1 day) to 3 (most or all of the time, 5-7 days)

Measures

ESM Negative Emotion

The datasets differed in how many items were used to assess intensity of negative emotions, but they all used multiple items with unipolar scales (see Table 4.1). We rescaled emotions from Dataset 1 and 2 to a scale range of 0 to 100 to match that of Dataset 3 to facilitate comparisons of results.

Momentary Indices Calculated from ESM Measures

Emotion Transition. In previous studies about emotion transitions, participants were coded as displaying only one type of emotion at a time, resulting in a category variable of emotion (Hollenstein et al., 2004; Van der Giessen et al., 2015). As a result, transitions were dichotomous: there was either a complete transition (as in Figure 4.1A) or no transition (as in Figure 4.1D). In contrast, our ESM emotion data were collected on scales that resembled continuous scales (e.g., 0 to 100 in Dataset 3). This allows for co-occurrence of emotions without transitions (Figure 4.1B) and partial transitions between emotions (Figure 4.1C).

A unifying way to operationalize transitions across both categorical and continuous data is to see transitions as a *compensatory* process between emotions as components in an emotion system. This idea is adapted from ecology, where transitions in an ecosystem are characterized by the compensatory replacement of one species by another across time or space (Choi et al., 2004; Doncaster et al., 2016; J. Wang et al., 2023). Alongside species replacements, there can be total population changes, such as increases in the total number of organisms across all species, a phenomenon described in ecology as nestedness (*nested* population changes). To delineate replacement against nestedness, ecologists have long made use of Bray-Curtis dissimilarity (Baselga, 2013b; MacGregor-Fors et al., 2022). Bray-Curtis dissimilarity is given by the sum of its two subcomponents, replacement and nestedness, which respectively measure compensatory replacements and nested population changes.

By drawing a parallel between emotions within an emotion system and species within an ecosystem, emotion transitions can be viewed as a compensatory process similar to ecological replacement. For this reason, we quantified negative emotion transitions using the replacement subcomponent of the Bray-Curtis dissimilarity[3]. As the replacement subcomponent is central to our hypotheses, we introduce it before returning to the nestedness subcomponent in the next subsection.

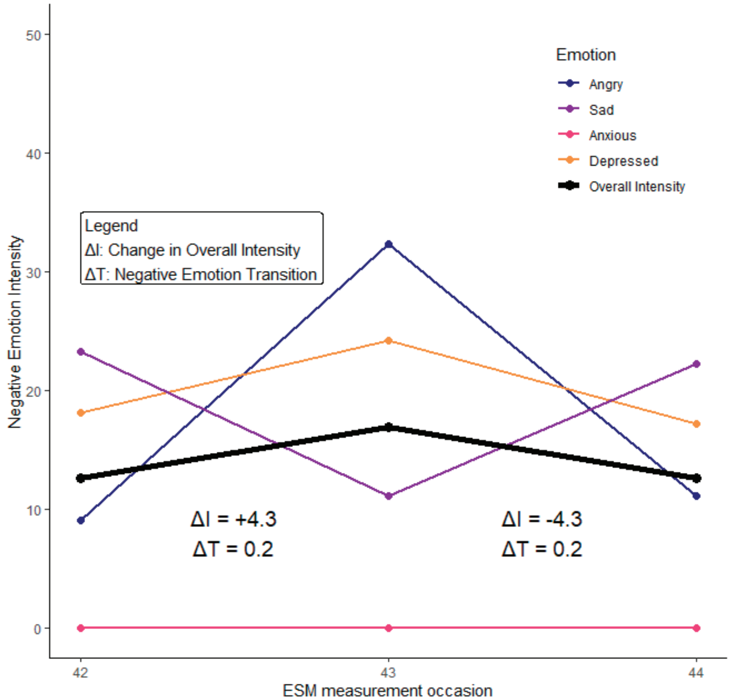
3 In Supplemental Material 3, we describe several alternative indices for measuring emotion transitions and explain why the replacement subcomponent align most closely with the construct of emotion transition we aimed to capture.

We calculated replacement with an R script adapted for ESM data (Lo et al., 2024). This script builds on the *betapart* package, originally developed for detecting compensatory replacements in ecological research (Baselga et al., 2022). The R script reliably detects replacement in simulated ESM data (Lo et al., 2024). Empirically, it has been used in ESM studies on emotion regulation and negative emotions (Li, Wylie, et al., 2024; Lo et al., 2024; Zhu et al., 2025). The replacement subcomponent ranges from values of 0 (no transitions, as in Figures 4.1B and 4.1D) to 1 (complete transitions, as in Figure 4.1A). To avoid division-by-zero errors, we added a small constant (0.001) to every intensity before using *betapart*. This way, two observations with all emotions rated zero still return a replacement subcomponent of 0, indicating that no transition occurred. In the Appendix, we walk through the formula to calculate replacement and provide calculation examples using Figures 4.1A to 4.1D.

We give a real-world case-example of how emotion transitions look like in Figure 4.2, which includes three measurement occasions from one participant in Dataset 2. The plot displays four negative emotions (anger, sadness, anxiety, and feeling depressed) along with overall negative emotion intensity and transition values calculated using the replacement subcomponent. Transitions are visible between measurements (the replacement subcomponent value is around .2 for both time lags), as lines for different emotions shift in compensatory ways, crossing one another. These examples show that emotion transitions can occur alongside both increases and decreases in overall emotional intensity.

Figure 4.2

Excerpts of three ESM measurements from a participant from Dataset 2.



Note. Negative emotion intensity is on a scale from 0 to 100. Across three measurement occasions, there are clearly emotion transitions: sadness first decreased, then increased. In contrast, anger and depression first increased, then decreased, which was compensatory to changes in sadness. Throughout, the participant consistently rated anxiety as zero. This figure also highlights two features of the replacement subcomponent. First, it accommodates measurements where one emotion (such as anxiety here) is always rated at zero intensity. Second, when three or more negative emotions are tracked simultaneously, the method can detect that a replacement occurred but not which exact pair of emotions exchanged intensity. For example, between measurements 42 and 43, a transition value of .2 could represent a decrease in sadness offset by an increase in either anger or depression, though the specific pairing cannot be uniquely identified.

Overall Intensity of Negative Emotions. We calculated the overall momentary intensity of negative emotions by the mean of intensity of emotions (e.g., in Dataset 2, overall intensity of negative emotions is the mean of *angry*, *sad*, *anxious*, and *depressed*), with higher scores reflecting a higher intensity. Satisfactory omega reliability within (.68 to .76) and between participants (.93 to .94) supported the use of momentary overall intensity of negative emotions as the outcome variable of our hypotheses.

We used the overall intensity of negative emotions as the outcome variable but not the nestedness subcomponent of Bray-Curtis dissimilarity, which is produced alongside in calculating the replacement subcomponent (i.e., emotion transitions) when using the *betapart* package. The nestedness subcomponent captures the overall magnitude, but not the direction of intensity change. Our transition-intensity reduction hypothesis expects that emotion transitions are accompanied by intensity reductions in negative emotions. However, because the nestedness component could only indicate that emotions changed, but not whether there was an increase or decrease, we could not use this component to test for intensity reduction. In Supplemental Material 2, we illustrate how to calculate the nestedness subcomponent and the full Bray-Curtis dissimilarity index obtained by summing nestedness and replacement. We do not describe nestedness in detail here because it served only as a covariate in our analyses and excluding it did not affect our main conclusions (see Supplemental Material 6).

Depressive symptoms

Levels of depressive symptoms were assessed with the 20-item Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977). Dataset 1 used a validated German translation of CES-D (Hautzinger & Bailer, 1993); Dataset 2 and 3 used a validated Dutch translation of CES-D (Wu et al., 2016). The differences in answering scales of the two versions are stated in Table 4.1. Example items are "I felt depressed" and "I was bothered by things that usually don't bother me". We calculated mean scores for these scales. We harmonized the score range across the three datasets from 0 to 1 to facilitate comparison of effect sizes across datasets. Internal consistencies calculated using Revelle's omega for each dataset were excellent: Dataset 1: .94; Dataset 2: .93; Dataset 3: .91.

Analysis

In preparation of testing our within-person hypotheses, each momentary index was separated into a within-person component (i.e., raw score minus the person-mean) and a between-person component (i.e., person-mean minus the grand-mean). The within-person component is time-varying and indicates a person's temporal fluctuations. The between-person component is time-invariant and indicates a person's difference from others (Bolger & Laurenceau, 2013).

We ran two multilevel models for each of the three datasets. In each model, ESM measurements (Level 1) were nested within participants (Level 2) and overall emotion intensity was the outcome variable. We specified Model 1 to test Hypothesis 1. To examine the impact of emotion transition (t-1 → t) on subsequent emotion intensity (t) across the sample, we included the fixed effect of emotion transition at the within-person (Level 1) and between-person (Level 2) level. We controlled for lagged negative emotion intensity (t-1; as measured at the previous time point) as a within-person fixed effect, so that we could examine whether emotion transitions (t-1 → t) were concurrent to *changes* in intensity from t-1 to t (as done in e.g., Lo et al., 2025). Following a common practice analyzing ESM data, emotion transitions between two observations overnight were excluded (e.g., Lo et al., 2025). The replacement and nestedness subcomponents add up to form the full index of Bray-Curtis dissimilarity and are recommended to be analyzed together (Lo et al. 2024). Therefore, we controlled for the nestedness subcomponent (within-person correlation with negative emotion intensity = -.10, .03, and -.01) at the within-person (level 1) and between-person level (level 2). Further, to control for any systematic time trends in the data, we added the fixed effect of time (centered, e.g., by setting the 35.5th observation for a person who reported over 70 observations). We modelled random effects (intercept and slopes) and allowed them to covary. We included a first-order autocorrelation structure on the residuals. Given the lack of consensus on handling missingness in temporally-dependent ESM data (J. Fritz et al., 2024), we excluded missing observations from analysis without imputations. We used the *nlme* package (Pinheiro et al., 2022) to estimate multilevel models with the quasi-Newton optimizer, a computationally efficient option.

We specified Model 2 to test Hypothesis 2. We extended Model 1 by including the main effect of depressive symptoms and cross-level interaction between emotion transition (Level 1) and depressive symptoms (Level 2) as predictors. We similarly introduced a cross-level interaction between the control variable (nestedness subcomponent, Level 1) and depressive symptoms (Level 2). In our analyses, we were primarily interested in the fixed effects of the within-person component of emotion transition on overall intensity in the baseline model (Hypothesis 1) and the cross-level interaction between emotion transition and depressive symptoms in the extended model (Hypothesis 2). Statistical significance was determined by examining whether fixed effects differed from zero at $p < .05$. If the interaction effect was significant, we (a) conducted simple slope analyses with the *reghelper* package (Hughes & Beiner, 2023) and (b) used the marginal-effects approach to visualize the levels of depressive symptoms at which negative emotion transitions started to significantly associate with changes in negative emotion intensity (C. J. McCabe et al., 2018).

Sensitivity analyses

We ran six sets of sensitivity analyses. First, to examine whether our findings were distorted by extreme outliers, we drew 1,000 bootstrapped samples from each data set to obtain a confidence interval of the effects which Hypothesis 1 and 2 concerned. Second, to examine whether our results were disproportionately contributed by a particular emotion, we conducted leave-one-out analyses by retesting our hypotheses with different scenarios of excluding an emotion item (e.g., excluding *sad* in Dataset 2 to inspect key estimates related to our hypotheses when the transitions to and from sadness – such as *sad-depressed* – were not included). Third, given that emotion transition is a within-person index by design and its values carry similar within-person interpretations (e.g., values of 0 and 1 respectively indicate no transitions and complete transitions for anyone), we retested our hypotheses with an alternative model specification without separating emotion transition into within-/between-person components. Fourth, although we analyzed the replacement and nestedness subcomponents of Bray-Curtis dissimilarity together as recommended (Lo et al., 2024; MacGregor-Fors et al., 2022), some ecological studies have used only the replacement subcomponent (Lennon et al., 2001). To account for this alternative practice, we retested our hypotheses using a model specification that included only the replacement subcomponent but not nestedness. We provide further justification in this alternative specification in Supplemental Material 5.

Additionally, we retested our hypotheses by controlling for emotion differentiation. We treated emotion differentiation as a potential confound because (a) its partial conceptual overlap with emotion transitions on the potential benefits of clarity in information and action-readiness, and (b) differentiation of negative emotions precedes increases in their intensity in hourly intervals (Lo et al., 2025). Negative emotion differentiation was calculated using the *emodiff* package (Erbas et al., 2021) with the same ESM negative emotion items we were analyzing.

Finally, we conducted time-lagged sensitivity analyses to further probe the temporal ordering of these associations. Specifically, we tested whether negative emotion transitions in a prior interval (t-2 to t-1) predicted changes in overall negative emotion intensity in the subsequent interval (t-1 to t). We also tested the reverse direction, namely whether changes in overall negative emotion intensity in a prior interval predicted negative emotion transitions in the subsequent interval.

Transparency and Openness

This paper follows the Workflow for Open Reproducible Code in Science (Van Lissa et al., 2021). We prepared our data and conducted all analyses in this paper in R (R Core Team, 2023). The three public datasets analyzed in this study, available on OSF (https://doi.org/10.17605/OSF.IO/MXJFH) and on EMOTE (request code: C7SC6HWU8R) have been analyzed by the lead author before (Lo et al., 2024; 2025). Given prior accesses, our hypotheses were not pre-registered. We did not conduct an *a priori* power analysis. Nevertheless, these datasets have been used in numerous published ESM studies examining within-person associations involving emotions (e.g., Blanke et al., 2020; Lo et al., 2024; 2025). On that basis, we judged the available sample sizes and number of observations to be sufficient for addressing our research question. The analysis codes of this study are available via https://osf.io/e6u97/?view_only=bcb17b2a5628401798685b4f2cb2ccc5.

RESULTS

Descriptive Statistics

The within-person correlations between distinct negative emotions ranged from .18 to .64 (Supplemental Material 4). Across three datasets, the intraclass correlation coefficients (ICCs) for overall negative emotion intensity (ICCs = .49, .48, and .42 from Dataset 1 to 3) and negative emotion transition (ICCs = .05, .10, and .08 from Dataset 1 to 3) indicated that 51%-90% of their variances were explained by differences within young adults (Table 4.2). These ICCs supported further within-person analysis as planned. Between young adults, depressive symptoms (CES-D; scaled 0–1 after harmonization) ranged from .02 to .86, M = .31, .25, and .21, and SD = .15, .16, and .13 in Dataset 1 to 3 respectively. Those who reported higher levels of depressive symptoms tended to have higher negative emotion intensity throughout the ESM study, but did not systematically differ in how likely they had negative emotion transitions (Table 4.2). In the two datasets with larger sample sizes, young adults with higher negative emotion transitions tended to report lower overall negative emotion intensity. This pattern was not evident in the smallest dataset.

Table 4.2

Descriptive Statistics of the Negative Emotion Indices and Depressive Symptoms in the Three Datasets.

									Between-person correlations [95% CI	
Variable	Possible range	*n*	Grand *M*	Min *M*	Max *M*	w*SD* *M*	b*SD*	ICC	1	2
1 Negative Emotion		3826	23.29	4.13	64.60	14.07	15.03	0.49		
Intensity	0-100	5682	14.92	2.51	48.59	10.01	10.88	0.48		
		12289	14.88	2.66	46.65	9.47	8.74	0.42		
2 Negative Emotion		3426	0.08	0.00	0.67	0.18	0.06	0.05	-.13 [-.35, .11]	
Transition	0-1	5147	0.14	0.00	0.68	0.18	0.07	0.10	**-.33 [-.50,-.13]**	
		11003	0.15	0.00	0.66	0.17	0.06	0.08	**-.25 [-.37,-.11]**	
3 Depressive Symptoms		70	0.31	0.04	0.86	-	0.15	-	**.58 [.40, .72]**	-.17 [-.39, .06]
	0-1	94	0.25	0.02	0.82	-	0.16	-	**.62 [.47, .73]**	**-.25 [-.43,-.05]**
		201	0.21	0.02	0.63	-	0.13	-	**.43 [.31, .54]**	-.09 [-.22, .05]

Note. Three rows of statistics refer to summary statistics of dataset 1, 2, and 3 correspondingly. Correlations are in bold if the 95% confidence interval does not contain 0. n refers to the number of ESM observations for all variables except for depressive symptoms, which refers to the number of young adults. bSD: between-person SD of within-person mean; wSD: mean within-person SD across all young adults.

Main Analysis

Using multi-level modeling, we first examined the main effect of negative emotion transition on negative emotion intensity (Model 1, Table 4.3). In all three datasets, negative emotion transition significantly predicted overall decreases in negative emotion intensity. Across all young adults, when the negative emotion transition reached 1, indicating a complete transition, their overall negative emotion intensity on average was reduced by 3.5 points on a 100-point scale. In other words, Hypothesis 1, the transition-intensity reduction hypothesis, was supported.

Table 4.3

Unstandardized estimates of fixed effects of the Model 1 and 2 that tested Hypothesis 1 and 2

	Fixed Effect Estimates [95% Confidence Interval]		
	Dataset		
	1 ($N = 70$, $n = 2936$)	2 ($N = 94$, $n = 4651$)	3 ($N = 201$, $n = 10000$)
Outcome: Negative Emotion Intensity $_{(t)}$			
Model 1			
Within-person (time-varying)			
Transition$_{(t-1 \rightarrow t)}$	-3.05 [-6.03, -0.07]*	-3.89 [-6.31, -1.48]**	-3.41 [-5.02, -1.80]***
Intensity $_{(t-1)}$	0.33 [0.27, 0.39]***	0.33 [0.28, 0.38]***	0.34 [0.30, 0.37]***
Between-person (time-invariant)			
Transition	-16.08 [-53.92, 21.76]	-22.07 [-42.03, -2.11]*	-29.17 [-42.28, -16.06]***
Model 2			
Within-person (time-varying)			
Transition$_{(t-1 \rightarrow t)}$	4.70 [-1.79, 11.19]	3.77 [0.18, 7.36]*	1.95 [-0.50, 4.41]
Intensity $_{(t-1)}$	0.33 [0.27, 0.39]***	0.33 [0.28, 0.38]***	0.34 [0.31, 0.37]***
Transition × Depressive symptoms	-27.67 [-49.64, -5.69]*	-31.43 [-50.28, -12.59]**	-29.20 [-41.22, -17.18]***
Between-person (time-invariant)			
Transition	4.70 [-1.79, 11.19]	3.77 [0.18, 7.36]*	1.95 [-0.50, 4.41]
Depressive symptoms	40.70 [24.53, 56.87]***	32.60 [20.63, 44.57]***	24.30 [16.04, 32.57]***

Note. The subscript "t" refers to the current moment, and "t-1" the previous moment. In Supplemental Material 5, we show full results of the models and their fit statistics (AIC, BIC, log-likelihood, and root mean squared error).

**: $p < .05$; **: $p < .01$; ***: $p < .001$.*

Next, using multi-level modelling, we examined whether depressive symptoms moderated the within-person relation between negative emotion transition and intensity change (Table 4.3). Model selection criteria (AIC, BIC, log-likelihood, and root mean squared error did not consistently favour Model 1 or Model 2 (Supplemental Material 5). Given the theoretical importance of examining negative emotion transitions both as a main effect and as moderated by depressive symptoms, we present and interpret results from both models.

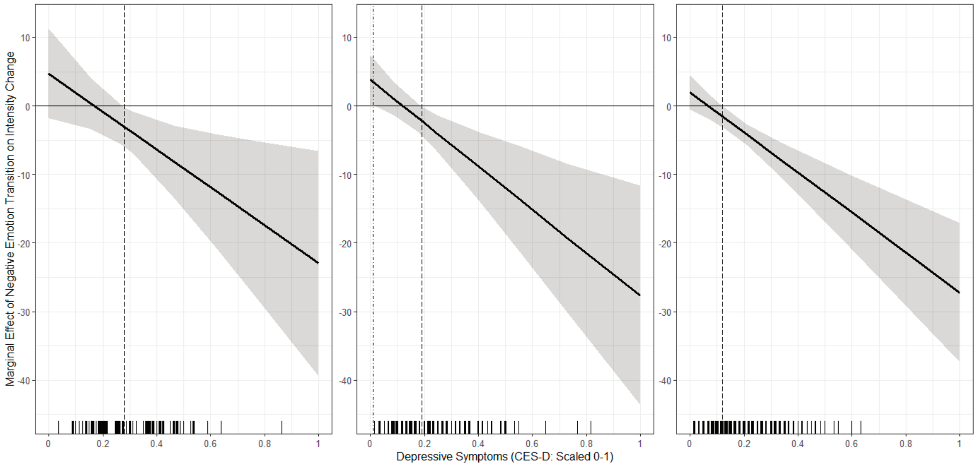
In Model 2, when the levels of depressive symptoms were added to the model, significant cross-level interactions emerged consistently across all three datasets: The levels of depressive symptoms moderated the transition-intensity reduction association.

We conducted simple slope analysis to clarify the strength of the transition-intensity reduction associations at different levels of depressive symptoms. Such associations were significant in young adults at mean (b = -3.88 [95% CI: -6.90, -0.86], -3.98 [-6.59, -1.37], -4.15 [-5.68, -2.62] for Dataset 1 to 3, all ps < .05) or one SD above the mean of depressive symptoms (b = -8.09 [-13.27, -2.90], -9.03 [-14.05, -4.01], -7.88 [-10.38, -5.38], all ps < .01), but not those at one *SD* below the mean of depressive symptoms (b = 0.32, [95% CI: -3.38, 4.02], 1.07 [-1.36, 3.50], -0.43 [-2.19, 1.32], all ps > .05). We visualized the regions of significant transition-intensity reduction using the shiny app by McCabe et al (2018). Results indicated that the within-person association between negative emotion transition and intensity change was significantly negative (i.e., significant transition-intensity reduction associations) starting from depressive symptoms levels .28, .19, and .13 (on a 0-1 scale; dashed lines in Figure 3) in Dataset 1 to 3 respectively, which represented 50%, 56%, and 69% of young adults in Dataset 1 to 3. For young adults below these levels, the associations between negative emotion transitions and intensity changes were not significant.

Overall, Hypothesis 2 was supported in all three datasets. Young adults with average and high depressive symptoms had transition-intensity reduction associations, whereas those who had low depressive symptoms did not. Across three datasets, half to two-thirds of participants exhibited transition-intensity reduction associations.

Figure 4.3

Marginal Effects Plots That Show the Regions-of-Significance of the Transition-Intensity Reduction Associations



Note. The vertical marginal rugs above the x-axes show the distributions of different levels of depressive symptoms in all datasets. The vertical dashed lines indicate the levels of depressive symptoms above which negative emotion transitions become significantly predicted decreases in negative emotion intensity, i.e., significant transition-intensity reduction associations. The dot-dash line in Dataset 2 indicates the level of depressive symptom below which young adults might have transition-intensity increase associations. None of the young adults in Dataset 2 were below this level. The 95% confidence region is indicated by the shaded area.

Sensitivity Analyses

Extreme Outliers. The bootstrapped confidence intervals of Hypothesis 1 and 2 did not contain zero, indicating that our findings were not due to extreme outliers (Supplemental Material 5).

Leave-One-Emotion-Out Analysis. We retested our hypotheses with different scenarios of excluding an emotion item. Despite estimates were often weaker when fewer number of emotions were included in this sensitivity analysis, 22 findings remained significant in all 26 possible leave-one-out scenarios (85%), meaning it was unlikely to have a single emotion (e.g., sadness) or transition pair (e.g., sadness-depressed) that is indispensable in the transition-intensity reduction associations (Supplemental Material 6). Furthermore, compared to leave-one-emotion-out models, the transition-intensity reduction estimates of our main analyses (with the complete number of emotion items) were often stronger and had narrower 95% confidence intervals (Figure S6). This was mostly the case in Datasets 1 and 2, which only had three or four negative emotion items. This indicated that including a more comprehensive list of negative emotions would likely result in stronger and more stable estimates.

Three Alternative Model Specifications. The findings remained mostly significant when (a) emotion transitions were not separated into within- and between-person components, (b) when the nestedness subcomponent (sensitive to intensity change without accounting for directions) was excluded as a covariate, or (c) when emotion differentiation was controlled for. These results added robustness to our findings as they held even after alternative analytical decisions or after accounting for how well people label their negative emotions (Supplemental Material 7).

Time-Lagged Models. Time lagged relations between negative emotion transitions and changes in overall negative emotion intensity were non-significant in both directions (Supplemental Material 8). These findings suggest that across intervals of 3 hours (in Datasets 2 and 3) and 6 hours (in Dataset 1), there was no evidence for a temporal ordering between negative emotion transitions and changes in negative emotion intensity.

DISCUSSION

Consistent across each of the three ESM datasets that encompassed 17,587 observations in 365 young adults, transitioning between negative emotions across hourly intervals was related to decreases in the overall intensity of negative emotions in the same intervals. Furthermore, this negative emotion transition-intensity reduction association was stronger among young adults with higher levels of depressive symptoms. Overall, our findings suggest that transitioning between negative emotions is beneficial in everyday life, especially for young adults with elevated depressive symptoms.

Consistent with Hypothesis 1, our findings provide empirical evidence that negative emotion transitions are linked to decreases in the intensity of negative emotions in daily life. This is consistent with recent evidence suggesting that negative emotion transitions are related to perceived emotion regulation success in daily life (Li et al., 2024). Even though having negative emotions occurring one after another can be unpleasant, each new emotion informs young adults about the situations, signals them their needs, and prepares them with emotion-specific action-readiness (Greenberg, 2006; Lench et al., 2015; Mauss et al., 2005; Schwarz & Clore, 1983). From the dynamic systems perspective, the transition-intensity reduction association is not surprising. Negative emotion transitions are thought to reflect *reactive* or *dynamic* flexibility in an emotion system depending on contexts (Hollenstein et al., 2013). Transitioning to a new emotion can reflect *reactive* responses to changing contexts, such as feeling angry after receiving a job-rejection email, or it can reflect *dynamic* adjustments within the same context that help a person stay engaged or influence the context, such as realizing that anger cannot change the job application outcome and transitioning instead to sadness about the wasted effort. It is plausible that during negative emotion transitions, young adults flexibly updated emotion-related information (e.g., situations, needs, and action readiness), allowing new emotions to arise in ways similar to how negative emotions are processed in psychotherapy (Pascual-Leone, 2009; Singh et al., 2021).

These findings extend prior work in two ways. First, earlier studies have shown that negative emotion transitions observed in laboratory conflict discussions are linked with reduced risks in long-term psychopathology (Hollenstein et al., 2004; Van der Giessen et al., 2015), and that transitions observed in psychotherapy precede short-term negative emotion intensity reductions (Singh et al., 2021). Our study bridges these to the everyday life of young adults, showing that there are also negative emotion transition-intensity reduction associations. Second, while the mood brightening literature focuses on *between-valence* dynamics, contrasting negative and positive emotions (Bylsma et al., 2011; Dejonckheere et al., 2018; Panaite et al., 2019), our study highlights the importance of *within-valence* transitions between negative emotions, which may be critical in regulating the overall intensity of negative emotions.

Transition-intensity reduction associations are stronger in young adults with higher levels of depressive symptoms

Consistent with Hypothesis 2, our findings suggest that transition-intensity reduction associations are stronger in young adults with higher levels of depressive symptoms. In other words, young adults with low-moderate to high levels of depressive symptoms benefit particularly from negative emotion transitions in reducing negative emotion intensity. These results extend three previous findings. First, they extend Maciejewski et al. (2023)'s recent work suggesting that individuals with depressive symptoms tend to report lower average levels of negative emotions if they exhibit higher variability in negative emotion intensity. Our results suggest that they do not only benefit from variability in the *intensity*, but also from variability in the *type* of negative emotions experienced (i.e., negative emotion transitions) which likewise predict intensity reduction. Second, our findings extend the "mood brightening effect," where individuals with higher depressive symptoms show stronger decreases in negative emotion intensity after events that elicit positive emotions (Bylsma et al., 2011; Panaite et al., 2019). Our findings indicate that such negative emotion intensity reductions may arise not only when there are between-valence, negative-to-positive emotion transitions, but also within-valence transitions between negative emotions. Third, our findings align with evidence from psychotherapy research in clinically depressed clients where negative emotion transitions precede negative emotion intensity reduction (Singh et al., 2021). In that context, transitions are thought to help clients depart from a dominant, change-resistant emotion. In contrast, our results, which held in the leave-one-emotion-out sensitivity analysis, indicate that the negative emotion transition-intensity reduction effect may not only apply to a single emotion, but also generalize across negative emotions more broadly.

Negative emotion transitions did not significantly associate with changes in intensity of negative emotions in young adults with no to low depressive symptoms. One interpretation is that young adults without depressive symptoms do not benefit from transitions in terms of reducing negative emotion intensity. However, alternative methodological explanations should also be considered. First, the low baseline of negative emotion intensity in young adults with no to low levels of depressive symptoms may explain the null result. With such low starting levels, there is limited room for further decreases, which weakens the observable transition–intensity reduction effect. Future research could address this by analyzing data collected during a period with a common stressor (e.g., approaching exam release, Dejonckheere et al., 2021), so that baseline intensity levels across all participants, whether depressed or not, are less subject to floor effects. Another alternative explanation concerns the temporal resolution of negative emotions' transitions and intensity reduction. Our time-lagged sensitivity analyses did not support a clear temporal ordering between negative emotion transitions and changes in intensity over 3-to-6-hour intervals. Instead, these processes may unfold over shorter time scales than our data could capture. Laboratory and psychotherapy research suggests that emotion transitions can occur over the course of minutes rather than hours (Van der Giessen et al., 2015; Singh et al., 2021). Among healthy individuals' daily lives, half of the episodes of temporarily heightened negative emotion intensity can recover within 0.5 to 2 hours (De Calheiros Velozo et al., 2023; Schreuder et al., 2024; Verduyn et al., 2009), meaning that one observation with elevated negative emotions can be followed by one with zero intensity in the current 1.5-to-3-hourly ESM sampling schemes. Even if there were transitions that accompanied fast intensity reduction in healthy young adults, they would remain "invisible" to our statistical models. In contrast, depressive symptoms are associated with slow recovery from heightened negative emotion intensity following stressful events in daily life (De Calheiros Velozo et al., 2023). Consequently, young adults with higher depressive symptoms may exhibit slower changes both in emotion intensity and in emotion transitions, making the transition–intensity reduction association more detectable within our ESM sampling intervals. To better test negative emotion transition-intensity reduction association, future research can analyze temporally granular data collected from healthy young adults, such as ESM data with burst periods that include a few frequent measurements (e.g., four measurements every 10 minutes; Schreuder et al., 2024) or high-frequency, minute-to-minute data from video-taped laboratory tasks.

Limitations and Future Directions

Interpretation of our results must consider several limitations. First, the generalizability of our conclusions depends on the range of emotion items included in the datasets. Our study only analyzed datasets with three (Dataset 1), four (Dataset 2), or six negative emotions (Dataset 3). Many other possible negative emotion transitions could have been missed (e.g., from shame to guilt). However, our sensitivity analysis of including fewer emotions for analysis suggested that including a more comprehensive list of negative emotions would likely result in stronger estimates. Therefore, while we acknowledge the datasets may not fully capture the breadth of negative emotional experiences, we expect our results to hold, if not become stronger, when a more comprehensive range of negative emotions is measured.

Second, we restricted our analyses to negative emotions. This decision was both theoretical and methodological. Theoretically, we focused on negative emotions because although prior daily life research has shown benefits of shifts from negative to positive emotions, much less is known about transitions between negative emotions themselves. Examining these understudied transitions can open a new avenue for exploring what accompanies or drives changes in overall negative emotion intensity. Methodologically, the replacement subcomponent cannot distinguish which emotions are driving the transitions and which are temporally leading the transitions (also refer to Figure 4.2 notes). Although our leave-one-emotion-out sensitivity analysis did not indicate that any single emotion disproportionately drove the observed transition–intensity reduction associations, it may still be clinically informative to know which specific emotion pairs contribute most strongly to these associations. Some pairs may be especially relevant, such as sadness to anger, given evidence that sadness tends to sustain in daily life and that eliciting anger in response to lingering sadness is recently suggested to reduce sadness (Nardone et al., 2025; Verduyn & Lavrijsen, 2015). Relatedly, applying the replacement subcomponent of Bray-Curtis dissimilarity to a mixed set of positive and negative emotions introduces additional interpretive challenges because within-valence (e.g., sadness to anger) transitions cannot be distinguished from across-valence transitions (e.g., sadness to happiness). However, understanding transitions between positive and negative emotions is crucial, given that moment-to-moment relations between positive and negative emotions is closely related to mental health (Bylsma et al., 2011; Coifman et al., 2012; Panaite et al., 2019; Rafaeli et al., 2007). Future work should methodologically advance Bray-Curtis dissimilarity to enable both quantification of pairwise contributions and clearer tests of across-valence emotion transitions.

Third, we cannot ascertain how much transitions of self-reported emotions in our study reflect transitions in the *experience* of emotions (e.g., from experiencing anger to experiencing sadness) versus the *labelling* of emotions (e.g., relabeling the same experience from anger to sadness). In our sensitivity analysis, our main results held after controlling for negative emotion differentiation, which is thought to reflect the labeling of emotions. Using multimodal assessment of emotions, future research may better ascertain the link between self-report and experience by checking if there are simultaneous changes in physiology alongside changes in self-reported emotions (Hoemann et al., 2020).

In this study, we purposely used three young adult samples with similar geographical, cultural and educational backgrounds for cross-validation. The theoretical underpinning of our study is not specific for young adults with these characteristics only. To broaden the generalizability of current findings, future studies should test our hypotheses in more diverse populations, including those of different ages, ethnic identifications, cultural backgrounds, and life phases (e.g., grieving or undergoing psychotherapy).

This study focused on depressive symptoms as a potential moderator of the negative emotion transition–intensity reduction association. This analytical focus was guided by the theoretical relevance of depressive symptoms to emotion transitions and the sampling design; participants were recruited based on pre-screened levels of depressive symptoms using a stratified sampling approach. To assess whether the transition-intensity reduction effects are transdiagnostic or specific to depressive symptomatology, future studies should compare the moderating role of depressive symptoms with other psychopathology (e.g., anxiety).

Implications

Given the novelty of our findings, further research is warranted to replicate our results across larger samples and diverse settings. Importantly, our analyses supported only concurrent associations between negative emotion transitions and reductions in negative emotion intensity within hourly intervals, not time lagged relations. Thus, the temporal ordering of these processes remains uncertain. Although our theoretical framing emphasized emotion transitions, we recognize that intensity reduction may sometimes come first. This may be especially likely in psychotherapy when negative emotion intensity is extremely high and the immediate priority is to reduce arousal and associated action tendencies (Lynch et al., 2006). In such cases, intensity reduction may precede later emotion transitions. Despite the uncertainty on temporal order between transitions and intensity reduction, four tentative clinical implications can be considered. First, if negative emotion transitions tend to precede reductions in overall negative emotion intensity, young adults with some depressive symptoms may benefit from having negative emotion transitions rather than focusing only on dampening intensity. While no systematic work has yet examined how such transitions occur in daily life, studies in structured interventions suggest that focusing on emotional experience, including its bodily sensations, action tendencies, and needs, can enhance the access of new negative emotions and intensity reduction (Crosswell et al., 2017; Nardone et al., 2025; Price & Hooven, 2018). It is important to note that these studies occurred in structured, social, and safe settings, so identifying a suitable context is likely critical to the facilitation of emotion transitions. Second, if reductions in negative emotion intensity tend to precede transitions, then young adults should pay attention to emerging new negative emotions as intensity of the original negative emotion decreases. New emotions may provide new information about their needs and may signal that a different response is now required, as suggested by recent experimental evidence showing that individuals perceive different strategies to be differentially useful for reducing anxiety versus sadness (Shu et al., 2021). Third, clinicians who work with young adults and have been collecting data in routine procedures (e.g., mood diaries or other daily-life monitoring tool Bos et al., 2022; Kazantzis et al., 2010; Lichtwarck-Aschoff et al., 2023), may be able to observe negative emotion transitions in clients' daily lives. Interpreting these transitions alongside clinical observations and interviews data may offer insight into clients' risk (e.g., absence of transitions, indicating inflexibility) and progress (e.g., transitions accompanied with symptom reduction). Fourth, clinicians can attend to negative emotion transitions that occur during sessions. When such transitions appear adaptive in symptoms or negative emotion intensity reduction, they can help clients understand how these occurred and find ways to recreate similar conditions outside of therapy (Kazantzis et al., 2010; Ryum et al., 2023). Such transfers of in-session learning to everyday contexts can then be monitored as outlined in the second implication. Overall, these implications are not meant to replace but complement existing effort and strategies in working with negative emotions in daily life.

Conclusion

This study is the first to investigate daily-life negative emotion transitions. Consistently across three samples, we found that negative emotion transitions within hourly intervals accompanied decreases in emotion intensity in the same intervals within young adults. Such decreases were greater for young adults who had higher levels of depressive symptoms. Our findings suggest that negative emotion transitions, the changes in the type of negative emotions, may be closely related to reductions in negative emotion intensity. Young adults who have elevated depressive symptoms, their clinicians, and researchers may want to explore whether, and in what ways, transitions between negative emotions are linked to reducing negative emotion intensity.

APPENDIX: CALCULATING THE REPLACEMENT SUBCOMPONENT OF BRAY-CURTIS DISSIMILARITY

Replacement subcomponent of Bray-Curtis dissimilarity $= 1 - \frac{\sum_{e \in E} min(x_{e(t)}, x_{e(t-1)})}{min\left(\sum_{e \in E} x_{e(t)},\ \sum_{e \in E} x_{e(t-1)}\right)}$ ...(1)

In Equation 1, *x* represents the set of all intensities of emotions across all measurement occasions for a given person. $x_{e(t)}$ denotes the intensity of emotion *e* (from the set of *E* measured emotions, e.g., anger and sadness in Figure 4.1) at time *t*, and $x_{e(t-1)}$ denotes the intensity of the same emotion at the previous time point (*t-1*). Equation 1 can be described in four calculation steps:

a) For each emotion, find the smallest of the two intensities across two time points. Add these intensities up. This step corresponds to the nominator in Equation 1, $\sum_{e \in E} min(x_{e(t)}, x_{e(t-1)})$.

b) Add up the intensity from all emotions within each time point. Take the smaller of the two totals. This step corresponds to the denominator in Equation 1, $min\left(\sum_{e \in E} x_{e(t)},\ \sum_{e \in E} x_{e(t-1)}\right)$.

c) Divide the unchanged intensity from step (a) by the smaller total from step (b). This step corresponds to the ratio in Equation 1.

d) Subtract that ratio from 1 (i.e., 1 minus step (c)). This gives the replacement value.

Consider the calculation steps using the two-emotion example from Figure 4.1C. Step (a) sums the lowest intensity of each emotion across the two time points. Anger decreases from 6 to 4, so the smaller intensity is 4. Sadness increases from 0 to 2, so the smaller intensity is 0. Step (a), the units of intensity that remains similar across time, is therefore 4 + 0 = 4. In step (b), we take the smallest of within-time point total intensity. T1 has a total intensity of 6 + 0 = 6. T2 has a total intensity of 4 + 2 = 6. They are equal, so we take 6 as the denominator as described in step (b). Step (c) divides step (a) by step (b): 4 ÷ 6 = 0.67. Step (c) is a ratio that indicates how similar the two time points. Step (d) takes 1 minus the similarity ratio from step (c) to obtain the replacement subcomponent: 1 – 0.67 = 0.33.

Table A1 shows these calculation steps for Figure 4.1A to 4.1D. Although these calculation steps are exemplified with two-emotion transitions, the replacement subcomponent readily extends to cases with more than two emotions.

Table A1

Calculating Negative Emotion Transitions in Figure 4.1 Examples

	Anger Intensity		**Sadness Intensity**		**Equation 1 in four steps (a to d) to calculate emotion transition with the replacement subcomponent of Bray-Curtis dissimilarity**			
	T1	T2	T1	T2	(a) = sum of **the lowest intensity** for each emotion at T1 or T2	(b) = minimal total of T1 or T2 sum of intensity across emotions	(c) = (a) / (b)	(d) = 1 – (c) = replacement
Figure 4.1A	6	**0**	**0**	6	0 + 0 = 0	6 + 0 = 6	0	1
Figure 4.1B	6	**6**	**0**	6	6 + 0 = 6	6 + 0 = 6	1	0
Figure 4.1C	6	**4**	**0**	2	4 + 0 = 4	6 + 0 = 6	0.67	0.33
Figure 4.1D	6	**6**	**0**	0	6 + 0 = 6	6 + 0 = 6	1	0

Note. T1 and T2: measurement occasions in Figure 4.1. **Intensities in bold** are the smallest intensities per emotion across two time points, which are summed to arrive at step (a). Intensities underlined belong to the time points that give the smallest sum of intensity, which are summed to arrive at step (b).

5

Loneliness and Depressive Symptoms in Adolescents: A Multi-Timescale Examination

This chapter is based on:
Lo, T. T., Pouwels, J. L., Vink, J., van den Broek, N., Eltanamly, H., Maciejewski, D., & Verhagen, M. (in press). Loneliness and Depressive Symptoms in Adolescents: A Multi-Timescale Examination. *Development and Psychopathology*. Preprint: https://doi.org/10.17605/OSF.IO/RJAQ4.

ABSTRACT

Can feelings of loneliness and depression be adaptive for adolescents? Yes, suggests the Evolutionary Theory of Loneliness: initially, loneliness activates depressive responses for self-preservation. In turn, these feelings prepare adolescents for reaffiliation, thereby reducing loneliness (H1a: short-term *balancing* feedback loop). If this fails, loneliness and depressive symptoms may become long-term traits that exacerbate each other over time (H1b: long-term *reinforcing* feedback loop). Therefore, the short-term balancing feedback loop between loneliness and depressive symptoms may buffer against their long-term increases (H2: across-timescale influence). We tested these hypotheses in Dutch adolescents (M_{age_Wave1} = 12.9, SD_{age_Wave1} = 0.7, 53% female) using six-wave, half-yearly panel data (N = 774; 2017-2021) and 7-day, 1.5-hourly experience sampling data ($n_{subsample}$ = 84; mid-2021). Residual dynamic structural equation modeling revealed reinforcing feedback loops at both short-term (1.5-hourly) and long-term (half-yearly), supporting H1b but not H1a. Bayesian latent change score modeling supported H2: Adolescents who felt more depressed an hour after heightened loneliness showed smaller half-yearly increases in trait loneliness. However, this buffering effect was not predicted by the hourly depressed-to-loneliness relation, nor did either hourly relations predict half-yearly changes in depressive symptoms. Our findings suggest that feeling depressed shortly after loneliness may protect adolescents from long-term loneliness.

Keywords: Adolescence, Depressive Symptoms, Feedback Loop, Loneliness, Timescale

LONELINESS AND DEPRESSIVE SYMPTOMS IN ADOLESCENTS: A MULTI-TIMESCALE EXAMINATION

Adolescence is a transitional period marked by pubertal changes, shifting academic and vocational expectations, and rapidly transforming interpersonal relationships (Sawyer et al., 2018). These transitions can be challenging for social and mental health. Indeed, many adolescents experience heightened loneliness, defined as the perceived discrepancy between one's desired and actual social connections (Twenge et al., 2021). They also experience increased vulnerability to depressive symptoms, which can include low mood, lack of motivation, and disturbances in sleep, appetite, and functioning (Qualter et al., 2013; Shorey et al., 2022). Given the relatively high prevalence and co-occurrence of loneliness and depressive symptoms in adolescents (Cacioppo et al., 2006; Shorey et al., 2022; Twenge et al., 2021), there is an urgent need to clarify how they co-develop and potentially influence one another, to allow us to better support adolescents' well-being (Mund et al., 2025).

The ways loneliness and depressive symptoms influence each other may depend on the timescales of observation. In the short term, a *balancing* feedback loop is theorized to be in play in two steps: initially, transient loneliness increases depressed feelings[1] for self-preservation. In turn, these feelings prepare for reaffiliation that reduces loneliness. Without this short-term balancing feedback loop in place, adolescents risk long-term increases in loneliness and depressive symptoms. Furthermore, over the long term, loneliness and depressive symptoms are thought to exacerbate each other in a *reinforcing* feedback loop (Allen & Badcock, 2003; Balsters et al., 2013; Burholt & Scharf, 2014; Cacioppo & Cacioppo, 2018; Qualter et al., 2015; Starr & Davila, 2008; Steger & Kashdan, 2009)). This study tests the above dynamics within and across timescales in two steps. First, we examined the temporal bidirectionality between loneliness and depressive symptoms at two timescales: half-yearly (long-term), using a sample of 774 adolescents, and hourly (short-term; approximately every 1.5 hours), using a subset of 84 adolescents. Second, we tested whether these hourly dynamics in loneliness and depressed feelings were predictive of half-yearly changes in loneliness and depressive symptoms. By investigating how these timescales interconnect, this study aims to clarify how short-term emotion dynamics shape adolescents' long-term changes in social and mental health.

Do Loneliness and Depressive Symptoms Influence Each Other Differently Over the Short- and Long-Term?

Loneliness and depressive symptoms are distinct concepts, as they center on perceived social isolation and mood, respectively. But they do often overlap in experience: An ostracized adolescent may feel depressed in response to isolation, while an adolescent cop-

1 This study uses the term depressive symptoms and depressed feelings distinctively to separate long-term symptoms from short-term emotional states.

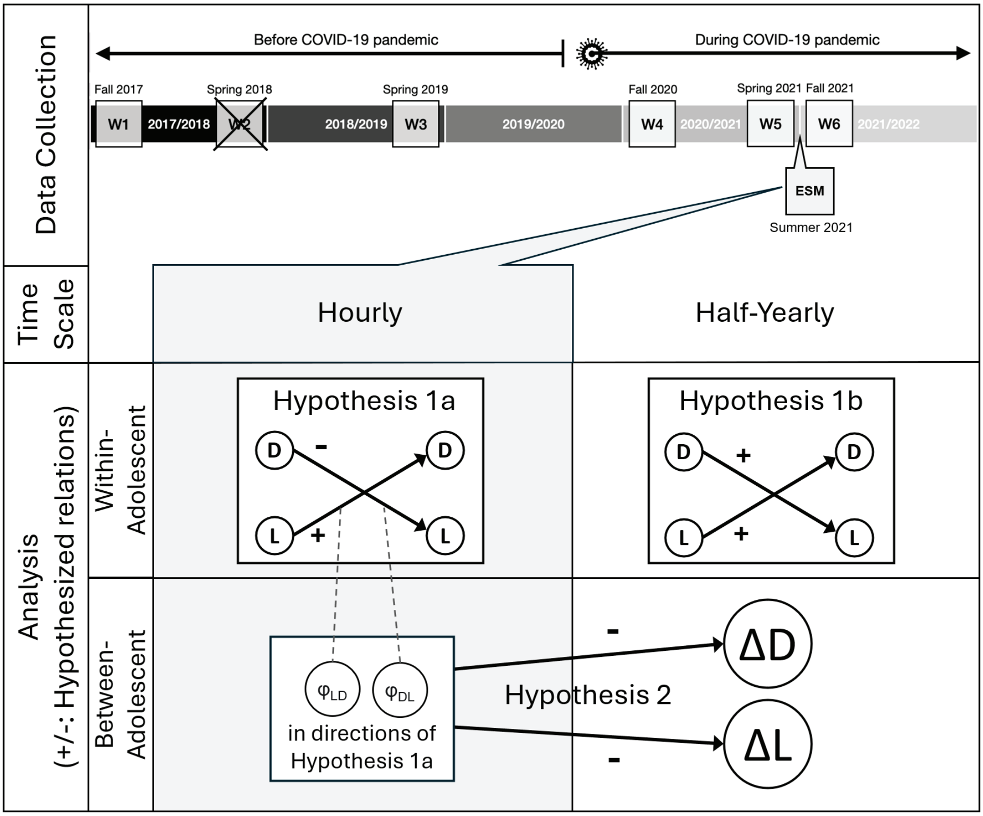
ing with depressive symptoms may feel lonely in enduring the burden from depressive symptoms (Cacioppo et al., 2006). This overlap suggests that loneliness and depressive symptoms may not only co-occur but also exert mutual influences over time.

Crucially, the nature and the direction of these influences may shift depending on the timescales of observation, such as hourly and half-yearly. This timescale dependency has been highlighted as a general principle in dynamic systems theories of developmental psychopathology (Granic, 2005; Lougheed & Keskin, 2021). For example, avoidance may reduce anxiety in the short term but maintain it in the long term (Hofmann & Hay, 2018). This same principle underlies the Evolutionary Theory of Loneliness (ETL, Qualter et al., 2015; Cacioppo & Cacioppo, 2018), which specifically theorizes how loneliness and depressive symptoms influence each other differently across short- and long-term timescales. According to the ETL, momentary fluctuations in loneliness can serve an adaptive function. When adolescents experience socially painful events—such as peer rejection— heightened loneliness signals their needs for reaffiliation. Before reaffiliation is taking place, however, loneliness can activate a coordinated set of responses, from neural to behavioural levels, aimed at promoting self-preservation. A transient depressive state is among such responses. In this state, adolescents tend to behave in a withdrawn manner, which helps them avoid further social rejection (Allen & Badcock, 2003). Importantly, depressed feelings may function as social signals, helping others perceive adolescents' needs for support and respond with affiliation (Allen & Badcock, 2003; Balsters et al., 2013). Through these processes, heightened loneliness initially increases depressed feelings, which in turn help to reduce loneliness, forming a short-term balancing feedback loop (Figure 5.1, Hypothesis 1a).

The short-term associations between loneliness and depressed feelings have recently been examined in Experience Sampling Methods (ESM) studies, which assess participants' feelings multiple times per day across several days or weeks in their daily lives. Studies on young to middle-aged adults have shown that momentary loneliness predicts increases in depressed feelings in subsequent hours or days (Kuczynski et al., 2024; Yung et al., 2023), but have not tested the reverse relation (i.e., depressed→loneliness effects). We are only aware of one study that tested the mutual influences between loneliness and depressed feelings in a four-hour window among university students' daily lives. This study found that momentary loneliness predicted increases in depressed feelings four hours later, but not in the opposite direction (Speyer et al., 2024). However, the previous study was conducted under strict COVID-19 restrictions, including schools and hospitality closures, making it unclear how these findings generalize to adolescents in daily life under less extreme COVID-19 restrictions. It is therefore warranted to study whether loneliness and depressed feelings influence each other bidirectionally in the short-term, to infer whether self-preservation and reaffiliation take place as the ETL would expect.

Figure 5.1

Overview of the Data Collection Timeline and Hypotheses (H1a, H1b, and H2)



Note. L: Loneliness; D: Depressive Symptoms; Δ: Change; φ_{LD} and φ_{DL}: Person-Specific Estimates of Within-Adolescent Temporal Relations (LD: Lonely→Depressed; DL: Depressed→Lonely) ESM: Experience Sampling Methods Study; W1, … W6: Wave of Panel Data Collection. W2 is crossed out because it did not measure loneliness nor depressive symptoms.

In contrast to this short-term balancing feedback loop, ETL posits that loneliness and depressive symptoms form a *reinforcing* feedback loop over a longer timescale (Figure 5.1, Hypothesis 1b). Prolonged loneliness may repeatedly activate depressive responses (Cacioppo & Cacioppo, 2018). Such repeated depressive symptoms negatively bias adolescents' perceptions of their social environments (Burholt & Scharf, 2014) and may strain peer relationships, as peers may get tired of the excessive demands from the depressive adolescents (e.g., seeking reassurance, Starr & Davila, 2008). The lower quality peer relationships may, in turn, lead to reduced support and may intensify feelings of social isolation (Steger & Kashdan, 2009)— thereby closing the long-term cycle of mutual reinforcement. Longitudinal studies empirically support this long-term reinforcing feedback loop, as loneliness and depressive symptoms predict one another across two months to one year later (Danneel et al., 2019; Lapierre et al., 2019; Lasgaard et al., 2011; Vanhalst et al., 2012). However, these earlier studies relied on traditional statistical approaches: the cross-lagged panel models. These traditional models treat all measurement values as representing within-person changes without disentangling within-person portions from time-invariant, between-person portions of measurement across time. As a result, these earlier studies likely had biased estimates that did not represent the actual within-person changes over time (Hamaker, 2023; Kristensen et al., 2023; Lucas, 2023). It is therefore warranted to re-examine the long-term bidirectional influences between loneliness and depressive symptoms with methods tailored to adequately capture within-adolescent changes.

Do Short-Term Dynamics Between Loneliness and Depressive Symptoms Shape Their Long-Term Changes?

Psychological processes can not only vary in direction and strength depending on the timescale, but may also exert influence from one timescale to another. From a dynamic systems perspective, processes linking loneliness and depressive symptoms may unfold on nested and interdependent timescales (Granic, 2005), a phenomenon also referred to as multiscale coupling (Jordan, 2013). In such a framework, short-term dynamics may gradually accumulate and shape longer-term outcomes. Two earlier studies were relevant to this across-timescale notion and our focus on social and mental health. Elmer et al. (2020) reported that middle-aged adults who behaviorally lingered in solitude (e.g., spending extended periods alone) were more likely to have increased depressive symptoms eight weeks later. Similarly, van Winkel et al. (2017) found that female adults whose hourly loneliness strongly lingered (e.g., one lonely moment strongly predicted the next) were likely to develop clinical depression over 20 months. These studies have focused on short-term dynamics *within* single socio-affective variables (i.e., solitude and loneliness), but from the ETL, we could infer that short-term dynamics *between* loneliness and depressed feelings may similarly exert across-timescale influence on social and mental health.

Specifically, if the lonely-depressed balancing feedback loop is working as theorized, adolescents should show rapid recovery from transient loneliness. As a result, balancing feedback loops may buffer against long-term increases in loneliness or depressive symptoms in adolescents. In other words, effective shorter-term regulation may interrupt the longer-term reinforcing loop. To date, however, no studies have directly tested this across-timescale influence expected by the ETL.

The Present Study

Drawing on dynamic system theories and the ETL, the present study tested two pre-registered hypotheses using data from a Dutch adolescent sample assessed across two timescales: hourly and half-yearly (https://osf.io/ru48z/?view_only=24f225f5d8c64985bd8131677437198b, Lo, Pouwels, et al., 2025). To distinguish short-term emotional states from longer-term symptomatology, we use the term depressed feelings to refer to momentary reports of feeling depressed at a specific time point, and depressive symptoms to refer to a broad continuum of symptom severity, ranging from nonclinical to clinical levels, assessed over longer intervals.

In the first Hypothesis (H1), we examined if there were hourly (H1a) and half-yearly (H1b) bidirectional temporal associations between loneliness and depressive symptoms that were consistent with mechanisms described by the ETL. H1a[2] posits an hourly balancing feedback loop: momentarily heightened loneliness is expected to predict increases in subsequent depressed feelings, while momentarily heightened depressed feelings are expected to predict decreases in subsequent loneliness. H1b posits a half-yearly reinforcing feedback loop, in which heightened trait loneliness predicts increases in trait depressive symptoms over six months, and vice versa. In Hypothesis 2 (H2), we assessed whether short-term processes shape long-term change. H2 states that adolescents with strong hourly balancing feedback loops between loneliness and depressive symptoms are protected from their half-yearly increases. With H2, we expected that the stronger the hourly person-specific estimates align with the directions expected by H1a (i.e., the more positive the lonely-to-depressed temporal relation, and the more negative the depressed-to-lonely temporal relation), the smaller the half-yearly increases[3] in trait loneliness and depressive symptoms would be. Building on our pre-registered hypotheses, this study also explored whether the effects tested in the hypotheses differed by sex, as sex differences may emerge during adolescence on how depressive symptoms and interpersonal functioning influence each other (Gadassi & Rafaeli, 2015; Rose & Rudolph, 2006).

METHODS

Participants and Procedures

The study utilized data from Dutch adolescents participating in the G(F)ood Together project (van den Broek et al., 2023). Although the longitudinal study and ESM study recruited parent-adolescent dyads, in the present study only data from adolescents were analyzed. Adolescents could participate only with active consent from both parents and adolescents.

2 H1a encompasses $H1_{LD\_ESM}$ and $H1_{DL\_ESM}$ in the pre-registration; H1b encompasses $H1_{LD\_Panel}$ and $H1_{DL\_Panel}$ in the pre-registration.

3 Assuming timescales are interdependent, one might expect individual differences (heterogeneity) in hourly and half-yearly feedback loops to be associated with each other, for example adolescents with stronger hourly balancing feedback loops between loneliness and depressed feelings are protected from their half-yearly reinforcing feedback loops. However, as shown in Figure 5.1, the ESM study was conducted in the summer of 2021, near the end of the six waves of longitudinal assessments spanning 2017 to 2021. Because the hourly data were collected later in time, they could not be used to explain heterogeneity of half-yearly feedback loops which was estimated with temporally earlier measurements.

Longitudinal Data (Testing Hypothesis 1b, Half-yearly Timescale)

A total of 783 adolescents were recruited together with their parents throughout the six-wave longitudinal study. The majority started their participation in Wave 1 or Wave 2 through recruitment in seven secondary schools in the Southeastern parts of the Netherlands, except 17 of them who started only at Wave 4; they were recruited through online social media advertisements.

Six waves of panel data were collected from 2017 to 2021 (Figure 5.1). We could not include Wave 2 data because, by design, Wave 2 did not assess adolescents' loneliness and depressive symptoms but other variables in the G(F)ood Together project irrelevant to this study. At each wave, adolescents received a small gift for their participation. Gift vouchers (ranging in value from €5 to €50) and three weekend getaways (of value €250) were raffled among the participating families. In addition, adolescents in Wave 5 and Wave 6 received €5 and €10 vouchers, respectively. The sample sizes per wave of data collection were: 667 (Wave 1), 674 (Wave 3), 306 (Wave 4: partial reopening between the first and second COVID-19 lockdown), 142 (Wave 5: the second COVID-19 lockdown), and 129 (Wave 6: partial reopening between the second and third COVID-19 lockdown). In Wave 1 to 3, participants completed surveys through Qualtrics Survey Software in school classrooms with the researchers' presence. Due to COVID-19, Wave 4 to 6 were completed online, which resulted in relatively more drop-outs. Drop-outs were predicted by older age, but not by sex nor educational level (van den Broek et al., 2024). Furthermore, equivalence tests showed that adolescents who did or did not drop out by Wave 6 had similar levels of Wave 1 loneliness and depressive symptoms (Supplemental Material 1). As pre-registered, we excluded 22 measurement occasions as potentially problematic in that participants answered all 10 items on depressive symptoms with the same rating when there were reverse-coded items. As a result, 9 participants had no data to be analyzed across the six waves. Hence, the final sample used for testing Hypothesis 1b consisted of N = 774 adolescents (M_{age_Wave1}= 12.88, SD = 0.67, 53% female; adolescents reported on their biological sex at Wave 1) with at least one complete wave of data. Most adolescents (98%) were born in the Netherlands. Among all adolescents, 39% of them had Dutch pre-vocational education, and 61% had Dutch higher general or pre-university education (van den Broek et al., 2024).

ESM Data (Testing Hypothesis 1a, Hourly Timescale)

Dyads of adolescents and parents who participated in Wave 5 were invited to enroll in the ESM study, resulting in 89 adolescent-parent dyads. The 7-day ESM study took place in June and July 2021, during a transitional period as COVID-19 restrictions were eased. Right before, between April and June 2021, adolescents had partially returned to in-person schooling and outdoor sports, marking a shift from the strict early-2021 lockdown with school closures and curfews (van den Boom et al., 2023). All participants used the SEMA-app (Version 3, Koval et al., 2019) on their mobile phones to receive momentary assessment notifications and complete ESM assessments. The ESM period spanned 7 days, from Monday to Sunday, during which participants completed ESM assessments 10 times a day. A semi-random sampling scheme was used. At 07:30 and every 90 minutes up to and including 19:30 (i.e., 07:30, 09:00, etc.) a notification was randomly scheduled within 30 minutes (i.e., 07:30-08:00, 09:00-09:30, etc.). The last notification was sent randomly between 21:00 and 21:30. Each ESM questionnaire expired 30 minutes after the notification, except the last notification, which was available for 149 minutes (i.e., until 23:59 at the latest). If participants did not respond to the notifications, they received two reminders 15 and 25 minutes after the initial notification (and after 75 and 145 minutes for the last notification).

Participating adolescents could receive €5 to €25, depending on the compliance of both adolescent and parent in the same dyad. Additionally, they entered into a raffle for two holiday vouchers of €250 value. Participants with low compliance received phone calls and WhatsApp messages to resolve technical difficulties that arose. According to our preregistered exclusion criteria, we excluded 5 adolescents because they consistently gave the same rating in all analyzed ESM items throughout the assessment week. In addition, 4 observations were excluded because the average response time was under 500ms per item, indicating potential careless responses (K. O. McCabe et al., 2012). As a result, our final sample consisted of $N = 84$ adolescents ($M_{age} = 16.43$, $SD_{age} = 0.6$, 57% female). The weeklong ESM study with 10 notifications per day resulted in 70 possible observations per adolescent. Adolescents completed on average 42 of 70 possible observations (60%, $SD = 25\%$, range = 4% to 97%). This sample was used to test Hypothesis 1a at the hourly level. To test Hypothesis 2, we included adolescents who had completed any of the last two longitudinal assessments and/or the ESM study that happened in between. We included participants with incomplete observations, rather than only those with complete data, so as to retain more information for Bayesian estimation. This resulted in a final sample of 181 adolescents.

Equivalence tests of adolescents' Wave 1 loneliness and depressive symptoms suggested that the subsamples for testing H1a ($N = 84$) and H2 ($N = 181$) were equivalent to the rest of the sample (Supplemental Material 1).

Measures

Trait Loneliness and Depressive Symptoms

Trait loneliness was assessed with the 12-item Louvain Loneliness Scale for Children and Adolescents: Friend scale (LEKA, Marcoen & Goossens, 1990), developed and validated in the Dutch-speaking context. Example items are "I feel isolated from others" and "I feel abandoned by my friends." Adolescents rated how applicable each item was to them on a 4-point scale from 1 ("Never") to 4 ("Often"). Higher scores indicate higher perceived discrepancy between one's desired and actual social connections.

Trait depressive symptoms were assessed with the Dutch translation of the Center for Epidemiological Studies Depression scale, 10-item short form (CES-D, Andresen et al., 1994). Example items are "I felt depressed" and "I was happy" (reverse scoring). Adolescents rated how well items described them in the past week on a 4-point scale from 1 ("Seldom or never [Fewer than 1 day]") to 4 ("Usually or always [5-7 days]"). Three positively-framed items were reverse-coded. Higher scores indicate higher depressive symptomatology.

Revelle's omega total of loneliness (.92, .95, .92, .91, and .94) and depressive symptoms (.81, .88, .89, .88, and .91) in the five measurements indicated the two scales had good reliability. To determine if the factor structures of the two scales were supported between and within adolescents, we ran multilevel confirmatory factor analysis on all LEKA and CES-D items across all measurements. Satisfactory fit indices showed that the factor structures held between adolescents and within adolescents across waves of measurement. Furthermore, longitudinal invariance tests suggested that the same factor loadings and intercepts could be assumed across waves (Supplemental Material 2). This indicated that it was appropriate to compare the traits across time. Given these results, we proceeded, as pre-registered, with the mean scores obtained from each scale. We transformed the range from "1 to 4" to "0 to 3" before further analysis for both trait scales.

State Loneliness and Depressed Feelings

State loneliness and depressed feelings were assessed with two ESM items that were "Right now I feel [lonely/depressed]" (used in Erbas et al., 2018) alongside seven other positive and negative affect items (content, relaxed, joyful, energetic, irritated, worried, and insecure; in each ESM prompt, adolescents alternated between reporting on positive and negative affect). Adolescents responded on an 11-point scale ranging from 0 to 10 ("not at all" to "a lot"). We assessed split-half reliability for each ESM item. To do so, we divided the time series by odd- and even-numbered calendar days, computing correlations between the two halves, and applying the Spearman-Brown prophecy formula to estimate time series reliability (Wendt et al., 2020). Reliability was high for both mean scores (lonely: .93, depressed: .90) and standard deviations (lonely: .76, depressed: .79).

Analysis

We followed our preregistered analysis plan (https://osf.io/ru48z/?view_only=24f225f5d8c64985bd8131677437198b, Lo, Pouwels, et al., 2025) to examine the bidirectional influences between loneliness and depressive symptoms in hourly and half-yearly timescales (Hypothesis 1) and the across-timescale influences from the hourly feedback loops between loneliness and depressed feelings on the half-yearly change in trait loneliness and depressive symptoms (Hypothesis 2). We prepared our data with R version 4.3.2 (R

Core Team, 2023) and conducted our analyses (Model 1a, 1b, and 2) in Mplus version 8.11 (Muthén & Muthén, 2017). Convergence of all models was assessed using the potential scale reduction (PSR) criterion, with values below 1.1 indicating acceptable convergence after a minimum of 5,000 iterations (e.g., Speyer et al., 2024). To check for stability of model convergence, we re-estimated the models by doubling the number of iterations needed for first-time convergence, inspected the smoothness of density plots of estimates, and examined the Bayesian posterior parameter trace plots of estimates.

We conducted a priori power analyses (https://osf.io/ru48z/?view_only=24f225f5d8c64985bd8131677437198b, Lo, Pouwels, et al., 2025). For H1a and H1b, which tested within-person processes, we estimated power using a random-intercept cross-lagged panel model (RI-CLPM) built from a reference dataset of Dutch middle adolescents. We chose RI-CLPM for three practical reasons. First, although RI-CLPM has a simpler structure than the dynamic structural equation models (DSEM) used in our primary analyses, in particular by excluding random slopes, it captures comparable within-person cross-lagged dynamics and has similarly been used in prior work for a priori power analysis when actual analyses involve more complex models (Bülow et al., 2025; McNeish & Hamaker, 2020). Second, using RI-CLPM allowed us to place our expected effects in the context of prior longitudinal studies on loneliness-depressive symptoms mutual influences that have largely relied on (RI-)CLPM. Third, recent work provides benchmarks for interpreting within-person RI-CLPM effects as small, medium or typical, and large (Orth et al., 2022),but similar benchmarks are not yet available for DSEM. Based on these power analyses, we had over 80% power to detect small-to-medium standardized effect sizes (.05) for H1a (hourly), and over 80% power to detect medium-to-large effect sizes (.08) for H1b (half-yearly). For H2, which tested between-person hypotheses, we conducted a power analysis with G*power with reference to the effect sizes in an across-timescale study (Elmer et al., 2020) and a guideline in interpreting individual difference effect sizes (Gignac & Szodorai, 2016) effect sizes. This analysis indicated over 80% power to detect a typical individual differences standardized effect size (.20).

Hypothesis 1: Hourly Balancing Feedback Loop (H1a) and Half-Yearly Reinforcing Feedback Loop (H1b)

To test Hypothesis 1a and 1b, we employed dynamic structural equation modeling (DSEM). DSEM was selected because it (a) accommodates multilevel time series data analysis with bivariate outcomes, (b) handles unequal measurement intervals, (c) uses all available observations without relying on listwise deletion, (d) uses latent centering of variables so that within-person changes can be more accurately modeled accounting for the individual differences in the stable components of the variables, and (e) provides standardized person-specific estimates for analyzing H2 (McNeish & Hamaker, 2020). Before we tested our main models, we checked whether there were any time trends in the data we should control for, by estimating a linear growth model for loneliness and depression. We had pre-registered that we would use *residual* DSEM (RDSEM) if time trends explained over 5% of within-adolescent variances in loneliness and depressive symptoms. RDSEM allows for modeling time trends in bivariate outcomes and models temporal effects between loneliness and depressive symptoms on their within-level residuals instead of the variables themselves, which leads to a more accurate estimation of variance terms.

Two main models were estimated. Model 1a tested the hourly balancing feedback loop (H1a) using the ESM data. Model 1b tested the half-yearly reinforcing feedback loop (H1b) using the panel data. Model 1a and 1b shared the same model structure, allowing for better comparison of parameter estimates between models in different timescales (Bülow et al., 2025). They differed only in the temporal resolution of the input data and in the inclusion of an additional time variable in Model 1b that marked the time passed since the onset of the COVID-19 pandemic. Supplemental Material 3 contains full model specifications.

Loneliness and depressive symptoms were latent person-centered, so that adolescents had person-specific estimates of their time-invariant latent person means. At the within-person level, the latent person-centered loneliness and depressive symptoms were regressed on time variables to account for the time trends (βs; see Supplemental Material 3). The resultant within-person residuals of loneliness and depressive symptoms followed a bivariate autoregressive cross-lagged specification so that the residuals of loneliness and depressive symptoms from a previous time point (t-1) influence themselves (autoregressive effects; φ_{LL} and φ_{DD}) and each other (cross-lagged effects; φ_{LD} and φ_{DL}, Figure 5.1) at the current time point (t). We set the time interval to 1.5 hours (ESM) and six months (panel data) using the TINTERVAL statement in Mplus to rescale time into 1.5-hour/half-yearly increments, so that we could consistently interpret the autoregressive and cross-lagged effect estimates as the carryover and spillover from 1.5 hours/half year prior to the assessment.

At the between-person level, we specified between-person variance around adolescents' average levels of loneliness and depressive symptoms across assessments (i.e., random intercepts), the average within-person effects of autoregressive and cross-lagged effects of residuals of loneliness and depressive symptoms (i.e., random slopes that allowed for heterogeneity in hourly and half-yearly cross-lagged effects), the average within-person effects of time trends, and the within-person residual variances. These random effects were loaded on a higher-order factor. This pre-registered approach was needed to achieve model convergence, as it could account for links between random effects akin to an unrestricted covariance structure between all random effects but with an advantage of simpler model specifications (McNeish & Bauer, 2022). Full model specifications are provided in Supplemental Material 3.

In testing H1a (hourly) and H1b (half-yearly), we were primarily interested in the within-person fixed cross-lagged effects: from the lag-1 residual of loneliness to that of depressive symptoms (φ_{LD}, Figure 5.1) and from the lag-1 residual of depressive symptoms to that of loneliness (φ_{DL}, Figure 5.1). These estimates tested the direction and strength of the bidirectional associations within individuals at both hourly and half-yearly scales above and beyond the time trends. This way, stronger estimates reflected greater subsequent deviations from adolescents' personal trends. We considered H1a supported if the 95% credibility interval of the hourly φ_{LD} estimate was positive, and that of the hourly φ_{DL} estimate was *negative*. We considered H1b supported if the 95% credibility interval of the half-yearly φ_{LD} and φ_{DL} estimates were *positive*.

From the output of Model 1a, we extracted standardized person-specific estimates of the cross-lagged effects between each adolescent's loneliness and depressed feelings (e.g., previous loneliness contributing to subsequent depressed feelings). These estimates were used to test H2.

Hypothesis 2: Adolescents with Stronger Hourly Balancing Feedback Loop Between Loneliness and Depressive Symptoms Are Protected From Their Half-Yearly Increases

To test Hypothesis 2, we specified Model 2, a Bayesian structural equation model (BSEM) using a latent change score (LCS) framework (Kievit et al., 2018). Specifically, Model 2 examined whether hourly person-specific cross-lagged estimates from Model 1a predicted half-yearly changes in trait loneliness and depressive symptoms from Wave 5 to Wave 6, because the ESM study occurred between these waves (Figure 5.1). Using BSEM[4] has advantages in not assuming specific distributions of parameters and residuals, making it particularly appropriate given the small sample sizes at the between-person level. Using the LCS modeling framework has advantages in accounting for individual differences in half-yearly changes and is less susceptible to measurement errors in observed variables (Kievit et al., 2018).

The outcome variables of Model 2 were the LCS in loneliness and depressive symptoms, ΔL and ΔD. The key predictor variables central to testing Hypothesis 2 were the person-specific estimates of hourly cross-lagged effects between loneliness and depressed feelings (φ_{LD} and φ_{DL}; Figure 5.1). Following the typical LCS framework, we included Wave

4 The preregistered analysis plan for H2 followed Elmer et al. (2020), who did a similar across-timescale investigation. This workflow involves two steps. First, (R)DSEM is estimated to capture hourly within-person relations. Second, person-specific estimates from (R)DSEM are carried forward to BSEM. Based on the suggestion of an anonymous reviewer, we ran a sensitivity analysis with a one-step approach in which the BSEM component is embedded directly in the between-person level of (R)DSEM (Hamaker et al., 2018). However, the one-step model did not converge (Supplemental Material 5). This nonconvergence is not surprising because our specification was more complex while supported by less data: we modelled two between-person outcomes with an average of 42 repeated measurements per participant (n=84), whereas the published one-step example used a single between-person outcome with roughly 100 repeated measurements per participant (N=101).

5 levels of loneliness and depressive symptoms, respectively, to predict their half-yearly latent changes. Residual variances in the change scores were estimated freely and were allowed to covary. The covariance between loneliness and depressive symptoms at Wave 5 was also estimated. Full model specifications are provided in Supplemental Material 3.

To test Hypothesis 2, we were primarily interested in the estimates of the paths from the person-specific hourly cross-lagged effects, φ_{LD} and φ_{DL} (Figure 5.1) to the half-yearly latent change scores in loneliness and depressive symptoms[5]. H2 stated that adolescents with strong hourly balancing feedback loops are likely to have half-yearly decreases in trait loneliness and depressive symptoms (i.e., protected from half-yearly increases). A balancing feedback loop consisted of positive φ_{LD} and negative φ_{DL}. Therefore, we considered H2 supported if the 95% credibility intervals of the across-timescale regression estimates from φ_{LD} to the latent change scores were negative (positive φ_{LD} multiplied with negative across-timescale effect gave decreases in trait loneliness or depressive symptoms), and the intervals of the estimates from φ_{DL} to the latent change scores were positive (negative φ_{DL} multiplied with positive across-timescale effect gave decreases in trait loneliness or depressive symptoms).

Exploratory analyses

To explore sex differences, we pre-registered conducting multi-group analyses based on the pre-registered models (Model1a, 1b, and 2). Because the multi-group analysis did not converge, we instead included sex (boys coded as 0 and girls as 1) as a time-invariant predictor in the models. In Model 1a and 1b, we regressed the person-specific temporal relations between loneliness and depressive symptoms on sex. In Model 2, we specified sex as a moderator in the paths of how hourly relations between loneliness and depressive symptoms predict their half-yearly changes. This was done by regressing the latent change scores on (a) sex and (b) two interaction terms between sex and person-specific hourly temporal relations (φ_{LD} and φ_{DL}). Sex differences were considered significant when the credibility intervals of these effects did not include zero.

5 Because the ESM study occurred three months after W5 and three months before W6, it was possible that person-specific estimates of the hourly feedback were influenced by factors we did not include in this study (e.g., social environments, Cacioppo & Cacioppo, 2018) or simply by loneliness and depressive symptoms at W5. Analytically, it was possible to specify additional regression paths in which person-specific ESM estimates of hourly loneliness and depressed feelings were predicted by W5 measurements of loneliness and depressive symptoms. We conducted a sensitivity analysis that added these additional paths to the H2 model. The results for H2 were unchanged. Furthermore, W5 loneliness and depressive symptoms could only account for less than 20% of the variance of the ESM estimates, indicating that person-specific hourly relations were mostly explained by factors other than W5 loneliness and depressive symptoms (see Supplemental Materials 5).

RESULTS

Descriptive Statistics

Table 5.1 includes descriptive statistics for state and trait loneliness and depressive symptoms. At both hourly and half-yearly timescales, adolescents reported relatively low average levels of loneliness and depressive symptoms, yet their variations across time (within-adolescent *SD*) and between adolescents (between-adolescent *SD*) were substantial relative to these means. Within the hourly timescale, positive skewness and kurtosis indicated that most observations clustered near the person mean, but when values exceeded the mean, they were likely to reach high levels. In contrast, half-yearly reports of loneliness and depressive symptoms were approximately symmetrical (near-zero skewness) with few extreme values (negative kurtosis). Both within and between adolescents, loneliness and depressed feelings were positively correlated at the hourly (r_{within} = .36, 95% CI [.33, .39]; $r_{between}$ = .75, [.64, .83]) and half-yearly (r_{within} = .36, [.33, .39]; $r_{between}$ = .56, [.51, .60]) timescales. Across-timescale correlations were estimated between traits (averaged across waves from 2017 to 2021) with states (averaged across one week of hourly assessments in mid 2021). (i.e., those between traits and states) These correlations were tested in the smaller ESM subsample (*n* = 84). There were positive between-adolescent correlations between trait depressive symptoms and state depressed feelings ($r_{between}$ = .45, [.26, .61]) or state loneliness ($r_{between}$ = .44, [.25, .60]). However, there were no significant correlations between trait loneliness and state loneliness ($r_{between}$ = .13, [-.09, .33]) or depressed feelings ($r_{between}$ = .21, [-.01, .40]). The intraclass correlation coefficients for trait and state loneliness and depressive symptoms ranged from .40 to .47 (Table 5.1), indicating that 53–60% of variance was explained by differences within adolescents across half-year or momentary intervals or measurement error. These within-adolescent variance justified further within-person analysis.

Model Adjustments Due to Time Trends

Loneliness and depressive symptoms significantly changed across time: they increased half-yearly across the longitudinal data collection period and decreased across the one-week ESM data collection period (Table 5.1; figures in Supplemental Material 3). Additionally, in the half-yearly data, the increase in loneliness accelerated after the onset of COVID-19 (i.e., Wave 4)[6], with no comparable change in depressive symptoms (Supplemental Material 4). The stationarity assumption did not hold, because time trends explained over 5% of within-adolescent variances in loneliness and depressive symptoms (5%–14%; Supplemental Material 3). Therefore, as pre-registered, we used RDSEM so that

6 The weak, non-significant correlations between trait loneliness and state loneliness or depressed feelings are understandable given the developmental time trend in trait loneliness from 2017 to 2021 and COVID-specific increases observed from fall 2020 (Wave 4) to fall 2021 (Wave 6). Because state loneliness was assessed during partial social restrictions in mid-2021, its levels likely diverged from those recorded in earlier years, reducing the correlations between the trait and state measures.

Table 5.1

Descriptive Statistics of Key Variables

Timescale	Variable (Possible Range)	N	T	Grand M	First M	W3 M	W4 M	W5 M	Last M	Time Trend EV%	Min M	Max M	wSD M	bSD	ICC	Skew-ness M	Kurt-osis M
Half-Yearly (Trait)	Depressive Symptoms (0-3)	769	1858	0.61	0.49	0.58	0.70	0.92	0.85	14%	0.39	0.79	0.27	0.42	.42	0.03	-2.46
	Loneliness (0-3)	774	1885	0.42	0.38	0.36	0.44	0.61	0.67	5%	0.23	0.60	0.25	0.44	.47	0.09	-2.43
1.5-Hourly (State)	Depressed Feelings (0-10)	84	3493	1.16	1.62	-	-	-	0.96	13%	0.15	4.96	1.31	1.30	.43	1.90	6.03
	Loneliness (0-10)	84	3494	0.97	1.75	-	-	-	0.80	9%	0.06	4.83	1.24	1.18	.40	2.24	7.67

Note. **T:** number of observations; First M: mean across all adolescents at Wave 1 or the first ESM observation; W3, W4, and W5: Wave 3 to 5; Last $\bar{x}$: mean across all adolescents at Wave 6 or the last ESM observation; Time Trend EV%: percentage of within-person variance explained by time trends; wSD: within-adolescent SD; bSD: between-adolescent SD; $\bar{x}$: between-person mean. ICC: intraclass correlation coefficient. The COVID-pandemic was in place between Wave 4 to Wave 6.

cross-lagged relations between loneliness and depressive symptoms (φ_{LD} and φ_{DL}) can be estimated without being biased by the time trends.

Pre-registered Analyses

Hypothesis 1: Feedback Loops between Loneliness and Depressive Symptoms Are Balancing at the Hourly Timescale (H1a) and Reinforcing at the Half-Yearly Timescale (H1b)

Using RDSEM, we first examined the bidirectional temporal effects between the residuals of loneliness and depressive symptoms in the hourly and half-yearly timescales (Table 5.2; see Supplemental Material 4 for full model outcomes). Loneliness was positively associated with subsequent increases in depressive symptoms, (Hourly φ_{LD} = 0.094, 95% CI [0.049, 0.139], Half-yearly φ_{LD} = 0.028, [0.013, 0.044]; standardized estimates), and vice versa (Hourly φ_{DL} = 0.072 [0.031, 0.113], Half-yearly φ_{LD} = 0.023 [0.012, 0.038]), indicating reinforcing feedback loops within both timescales. The results are in contrast with H1a (which expected a balancing feedback loop) but supported H1b. The magnitude of these cross-lagged effects differed across timescales. At the hourly level, the standardized cross-lagged estimates were comparable to the size of the estimated time trends in loneliness (β = -0.15 [-0.24, -0.10]) and depressed feelings (β = -0.14 [-0.30, -0.09]) but were small relative to their autoregressive estimates (φ_{LL} = 0.20 [0.14, 0.24], φ_{DD} = 0.23 [0.18, 0.28]), i.e., how deviations from time trends of loneliness and depressed feelings predicted themselves at the following measurement. At the half-yearly level, the cross-lagged estimates were small relative to the developmental and COVID-19-specific time trends (βs = –0.45 to 0.67). The cross-lagged estimates were also small relative to the autoregressive estimates of loneliness (φ_{LL} = 0.93 [0.91, 0.94]) and depressive symptoms (φ_{DD} = 0.92 [0.91, 0.94]). In summary, if adolescents had levels of one variable deviating from their own time trends (e.g., heightened loneliness), there were subsequent same-direction deviations in the other variable (e.g., subsequently heightened depressive symptoms), both at the hourly and half-yearly timescales.

In preparation for estimating Model 2, we extracted person-specific estimates of adolescents' hourly lonely→depressed and depressed→ lonely temporal relations. These hourly estimates were not significantly correlated (*r* = .14, [-.10, .54], Figure 5.2A). This indicated that an adolescent's hourly lonely→depressed relation was not predictive of their depressed→lonely relation. Consistent with this, very few adolescents showed a combination of positive lonely→depressed effects and negative depressed→lonely effects, as reflected by the near absence of points in the lower-left quadrant relative to the origin in Figure 5.2A.

Table 5.2

Standardized Effects and Credibility Intervals in Testing the Hypothesized Feedback Loops and Across-Time-Scale Influences

		Hypothesis 1 (H1a & H1b)		**Hypothesis 2 (H2)**
	Hypothesized Direction	Within-Adolescent Temporal Relations (Fixed Effect; Standardized)	Between-Adolescent Variance (Random Effect; Unstandardized)	Between-Adolescent Effects (Standardized)
Model 1a (H1a): Hourly Timescale ($n = 84$, $t = 3550$)				
Lonely → Depressed	+	**+.094 [.049, .139]**	.024 [.011, .047]	
Depressed → Lonely	-	**+.072 [.031, .113]**	.003 [.000, .025]	
Model 1b (H1b): Half-Yearly Timescale ($N = 774$, $t = 1880$)				
Lonely → Depressed	+	**+.028 [.013, .044]**	.001 [.000, .001]	
Depressed → Lonely	+	**+.023 [.012, .038]**	.001 [.001, .001]	
Model 2 (H2): Across-Timescale Influence ($n = 181$)				
Hourly Lonely → Depressed Predicting				
Half-Yearly ΔLoneliness	-			**-.284 [-.520, -.014]**
Half-Yearly ΔDepressive Symptoms	-			+.178 [-.045, .385]
Hourly Depressed → Lonely Predicting				
Half-Yearly ΔLoneliness	+			+.089 [-.192, .352]
Half-Yearly ΔDepressive Symptoms	+			+.152 [-.069, .351]

Note. Δ = Change. Standardized effects where credibility interval did not encompass zero are denoted in bold. See Supplemental Material 3 for full results.

Hypothesis 2: Hourly Balancing Feedback Loop between Lonely and Depressed Feelings Buffers Half-Yearly Increases in Trait Loneliness and Depressive Symptoms

Next, using BSEM with LCS, we examined whether the person-specific estimates of the hourly bidirectional temporal effects between lonely and depressed feelings predicted half-yearly changes in loneliness and depressive symptoms. Hypothesis 2 was partially supported (Table 5.2): the more positive adolescents' hourly lonely→depressed temporal relation was, the smaller half-yearly increases they had in loneliness (b^* = -0.28, 95% CI [-0.52, -0.01]). This indicates the stronger hourly coupling from loneliness to depressed feelings adolescents had, the more likely they had half-yearly decreases in loneliness (downward slope, Figure 5.2B[7]). However, this temporal relation was not related to changes in trait depressive symptoms (b^* = 0.19 [-0.04, 0.39], Figure 5.2C). Further, the reversed temporal relation (depressed→lonely) was unrelated to half-yearly changes in either trait loneliness (b^* = 0.10 [-0.19, 0.36], Figure 5.2D) or depressive symptoms (b^* = 0.16 [-0.06, 0.36], Figure 5.2E).

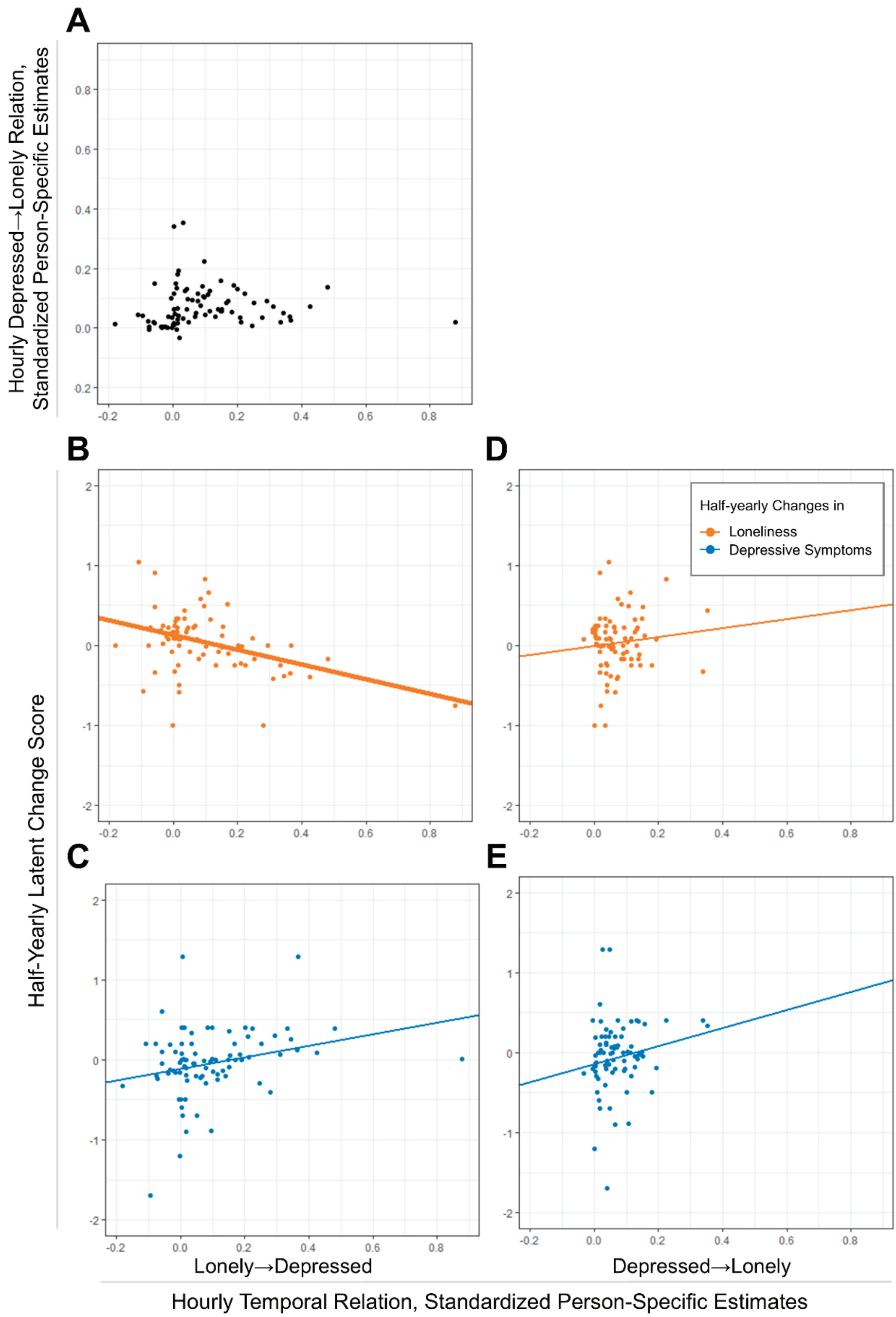
Exploratory Analyses: Sex Differences

Density plots of the person-specific estimates for H1a and H1b (Supplemental Material 4) were smooth and unimodal, suggesting no clear evidence of subgroup mixtures such as separate distributions for boys and girls. Even so, we examined potential sex differences by adding sex as a time-invariant predictor to Model 1a and 1b and as a moderator to Model 2. Estimates and credibility intervals of all exploratory results are available in Supplemental Material 4. Within hourly and half-yearly timescales, regression estimates from sex to within-adolescent temporal relations between loneliness and depressive symptoms were non-significant. This indicated that these within-adolescent temporal relations appeared similar across boys and girls. Across timescales, sex did not significantly moderate how hourly dynamics predicted half-yearly changes in loneliness and depressive symptoms. This indicated that all across-timescale effects appeared similar across boys and girls. Overall, there appeared to be no sex differences in all the effects we investigated.

7 We followed our preregistered plan by including data from all participants unless their responses indicated potential carelessness. At the request of an independent reviewer, we also explored the influence of participants with outlying person-specific ESM estimates by conducting sensitivity analysis on excluding outliers. The direction of the findings remained unchanged, although one additional path had a 95% credibility interval that excluded zero. We report and discuss these exploratory results in Supplemental Materials 5.3.

Figure 5.2

Person-Specific Estimates of Hourly Bidirectional Influences Between Loneliness and Depressed Feelings: Distribution and Relations to Half-Yearly Changes in Loneliness and Depressive Symptoms.



Note. Thick regression lines indicate statistically non-zero slopes.

DISCUSSION

Drawing on data from the same pool of Dutch adolescents assessed both hourly and half-yearly, we examined whether the temporal relations between loneliness and depressive symptoms at these two timescales aligned with the mechanisms proposed by the ETL. Within both timescales, we found reinforcing feedback loops: once loneliness or depressive symptoms were heightened, the other tended to increase in turn. Across timescales, we found that the more positive hourly lonely-to-depressed relations adolescents had, the lower their risk of half-yearly increases in loneliness. Although short-term increases in depressed feelings after loneliness may protect adolescents from long-term increases in loneliness, this buffering effect was not observed for the reverse hourly relation (increases in loneliness after feeling depressed), nor did either hourly process predict half-yearly changes in depressive symptoms.

Our findings offer partial support for the ETL in three ways. First, using RDSEM, a more robust statistical approach that separates within-person and between-person findings, we replicated earlier longitudinal studies that identified a reinforcing feedback loop between loneliness and depressive symptoms within adolescents over longer time frames (e.g., Vanhalst et al., 2012). These effects emerged even after accounting for adolescents' developmental trends, their adjustment during COVID-19, and how adolescents' loneliness and depressive symptoms temporally predicted themselves (i.e., autoregressive effects), although the reciprocal effects between loneliness and depressive symptoms were small relative to their developmental trends, COVID-19 specific trends, and autoregressive effects. This provides further support for the view that adolescents' social and mental health may co-deteriorate in a mutually reinforcing manner (Lau et al., 2025). Second, extending previous work on momentary temporal relations (Kuczynski et al., 2024; Speyer et al., 2024), our hourly results showed that heightened loneliness predicts subsequent increases in depressed feelings, which is consistent with the ETL. However, we also observed the reverse, that higher depressed feelings predict subsequent increases in loneliness, which contrasts with the ETL's expectation that depressed feelings facilitate decreases in loneliness. Third, we found that adolescents with a stronger positive hourly lonely→depressed relation showed smaller half-yearly increases in loneliness. Other across-timescale links we tested, including whether these hourly dynamics predicted half-yearly changes in depressive symptoms, were not supported. In examining interdependent timescales in developmental psychopathology (Granic, 2005; Jordan, 2013), our findings suggest that some short-term processes may play a more influential role than others in shaping long-term changes. In this case, the short-term coupling from lonely to depressed feelings, which even though it may be emotionally burdensome to adolescents, can protect adolescents from long-term loneliness. Given that the across-timescale effect sizes were relatively small and some effects were in opposite directions than expected, future research is warranted to replicate our findings across various timescales.

Clarifying the Evolutionary Theory of Loneliness

The ETL suggests that transient loneliness can be adaptive via a short-term balancing feedback loop: transient loneliness temporarily increases depressed feelings for self-preservation (Cacioppo & Cacioppo, 2018), and they collectively facilitate reaffiliation (Qualter et al., 2015), which brings loneliness back to baseline. In this loop, the lonely→depressed segment reflects adolescents' withdrawal from challenging social contexts (self-preservation). Our findings supported this segment of the ETL. At the hourly level, heightened loneliness predicted subsequent increases in depressed feelings. As a result, across timescales, this hourly lonely→depressed relation buffered half-yearly increases in trait loneliness. According to the ETL, the depressed feelings communicate a need for support, increasing the likelihood that supportive peers or caregivers offer their care. Through this process, adolescents may reaffiliate and meet their social needs, returning their loneliness to baseline and reducing the risk of having long-term loneliness.

In contrast, our findings did not support the ETL-expected loneliness-reducing effect in the hourly depressed→lonely relation. Instead, heightened depressed feelings predicted *increases* in loneliness an hour later. Moreover, this hourly dynamic did not predict half-yearly changes in loneliness or depressive symptoms. These unexpected results may be better understood in light of the specific timescales examined, competing emotional processes, and the broader social context in which the study was conducted. The first explanation for the absence of a negative hourly depressed→lonely effect might lie in the choice of measurement timescale. In the ETL, different paces in the two segments of the lonely→depressed→lonely balancing feedback loop could be inferred. The effect from loneliness to depressive symptoms was theorized to be part of the neural-to-behavioural coordinated set of responses that are quick in nature (Cacioppo & Cacioppo, 2018). In contrast, the proposed loneliness-reducing effect of depressed feelings is thought to operate socially via reaffiliation, which may unfold more slowly. Supporting this, recent multi-timescale studies suggest that it can take weeks before emotions shape interactions in relationships. For example, adolescents' negative emotions predicted increases in parent–adolescent conflict at a weekly timescale, but not at daily or biweekly intervals (Bülow et al., 2025). Similarly, depressive symptoms predicted increases in parent-adolescent conflict in biweekly intervals (but not at monthly, bimonthly, or three-monthly timescales; Bülow et al., 2025) and declines in parental support at biweekly and three-month intervals (but not at daily, annual, or biannual timescales; Boele et al., 2023). While little is known about whether peer support decreases in similar ways or increases as the ETL expects, changes in social relationships after feeling lonely and depressed might need more time. Instead of the hourly intervals in the current study, the loneliness-decreasing effect might be better studied in a daily or weekly interval.

This theory-measurement mismatch may also explain our null findings across timescales regarding the depressed→lonely effects: although the lonely→depressed hourly relation predicted long-term changes in loneliness, the depressed→lonely hourly relation did not. If the latter reaffiliation process unfolds over days or weeks, but not over the hourly intervals measured in the current study, such hourly dynamics would not hold predictive value on the expected long-term protective effect against loneliness and depressive symptoms. To refine the empirical testing of the ETL, future research should examine the short-term depressed→lonely relations across multiple timescales (e.g., hourly, daily, weekly) to identify the window in which loneliness-reducing effect most clearly manifests. Determining this time window not only addresses broader calls to refine developmental psychopathology theories by specifying their timescales (Hamaker, 2023), but is also crucial for effectively testing whether the short-term depressed→lonely relation contributes to long-term changes in adolescents' social and mental health.

A second explanation for the increase in loneliness after adolescents feel depressed is that this association may have captured competing processes not accounted for by the ETL. An example is spillover between negative emotions, which refers to a phenomenon where one negative emotion (e.g., depressed or angry) activates another (e.g., lonely or fear) over hours (Nencheva et al., 2024; Thornton & Tamir, 2017). Future tests of the ETL should aim to disentangle the theorized reaffiliation process from other competing processes. One promising avenue is to measure reaffiliation behaviours, such as active, engaging social interactions, alongside cognitive precursors such as adaptive attribution styles (Qualter et al., 2015) and features of social environments that facilitate reconnection (Cacioppo & Cacioppo, 2018). With these measures, researchers can examine the depressed→lonely association specifically on occasions when reaffiliation is enabled by cognitive or environmental conditions, and separately when reaffiliation has occurred through observable social behavior.

A third explanation for the absence of negative depressed depressed→lonely relations relates to the COVID-19 context in which the study took place. Because the ETL highlights reaffiliation as a key mechanism in reducing loneliness, it is important to consider the broader social context in which loneliness unfolds. Our findings extend the work by Speyer et al. (2024) about university students' loneliness and depressed feelings during a period of strict COVID-19 restrictions (e.g., closure of schools and hospitality). Although our ESM study was conducted in a COVID-19 period where in-person interactions were possible, some social restrictions remained (e.g., partial school resumption). During the COVID-19 pandemic, adolescents partly compensated for their lack of social interaction by increased social media use, but they found in-person interactions more satisfying and meaningful than online interactions (Parent et al., 2021; Van de Casteele et al., 2024). Therefore, this broader COVID-19 context might explain why the observed depressed→lonely relation was not negative as hypothesized in H1a: compared to non-pandemic times, adolescents may have had fewer offline opportunities to reaffiliate with supportive peers, limiting the ETL-expected loneliness-reducing effect of depressed feelings. This may also explain why there was an increasing trend in loneliness (but not depressive symptoms) across the final three half-yearly measurements of our study, a pattern also observed in other research on middle to late adolescents (Bamps et al., 2024; van den Boom et al., 2023). Now that the acute phase of COVID-19 pandemic is over, new studies can replicate our findings in how loneliness and depressive symptoms influence each other in typical, non-pandemic times.

The Potential Role of Sex

Exploring sex differences in how loneliness and depressive symptoms influence each other can inform us whether adolescents may benefit from sex-specific support in dealing with loneliness and depressive symptoms (Dunn & Sicouri, 2022). We found no evidence for sex differences in our within- and across-timescales findings. This aligns closely with recent work by Kuczynski et al. (2024) on short-term relations and meta-analytic evidence on long-term relations (from traditional cross-lagged panel model studies, (Z. Chen et al., 2023), both of which reported no support for sex differences in mutual influences between loneliness and depressive symptoms. Together, these results extend the ETL perspective by suggesting that not only the reaffiliative motive triggered by transient loneliness, but also the self-preservation responses, may operate similarly across the two sexes (Qualter et al., 2015).

Limitations

Our study has several limitations. First, our dataset did not have optimal reaffiliation-related variables for us to include in the model. Even if there were, our sample size was insufficient to support more complex modeling. As a result, we were unable to directly test the reaffiliation-related mechanisms of the ETL in the short-term lonely–depressed–lonely balancing feedback loop. Second, our current RDSEM model specifications only included two time points in each unit of analysis (Figure 5.1). Therefore, our results could not inform whether the two segments of the balancing feedback loop were sequentially chained (i.e., lonely→depressed→lonely) as the ETL theorized. Ideally, testing the balancing feedback loop would require a within-person mediation model that traces effects over multiple lags (e.g., lag-2 loneliness to lag-0 loneliness via lag-1 depressed feelings). This design likely demands larger samples and more intensive data due to the multiplicative nature of mediation estimates (see M. S. Fritz & MacKinnon, 2007 for a discussion on between-person mediation analysis, which in principle also applies with within-person mediation). Third, due to drop-outs during the COVID-19 pandemic, different subsamples were used to test our hypotheses. This has led to potentially underpowered tests, particularly for the testing of across-timescale effects and sex differences. To address these three limitations, future studies with larger samples, more observations, and richer data that measured reaffiliation should attempt to replicate and expand upon our findings.

Finally, measurement approaches across the two timescales were different. While the longitudinal study employed validated multi-item scales that were retrospective in nature, the ESM study relied on single-item measures of feelings at the assessed moments. This introduces some ambiguity as to whether differences in temporal relations across timescales are due to time resolution or measurement method. To tackle this, future studies may consider a combination of multiple approaches to assess loneliness and depressive symptoms (e.g., taking the mean values of these variables within an ESM period, van Winkel et al., 2017) and multiverse analyses (i.e., comparing results of the same research questions across alternative data processing procedures, Steegen et al., 2016). These strategies would help disentangle the impact of measurement features on concurrent validity, supporting more meaningful comparison of estimates derived from different timescales.

Conclusion

This study examined bidirectional influences between adolescents' loneliness and depressive symptoms within and across hourly and half-yearly timescales. Within both timescales, loneliness and depressive symptoms mutually reinforced each other over time. The half-yearly results align with the longer-term reinforcing feedback loop outlined in the ETL. The hourly findings, however, were only partially aligned with the ETL and the hypothesized short-term balancing feedback loop. Instead of the hourly intervals we examined, the loneliness-decreasing process of reaffiliation described by the ETL may unfold over longer intervals, such as days or weeks. Across timescales, hourly dynamics between loneliness and depressed feelings were not related to half-yearly changes in depressive symptoms. In contrast, adolescents were protected from half-yearly increases in loneliness if they showed stronger hourly increases in depressed feelings following heightened loneliness, although the reverse (hourly changes in loneliness following heightened depressed feelings) did not shape half-yearly changes in loneliness. Taken together, findings show that feeling depressed after transient loneliness, even though unpleasant, could be part of a normal process that supports adolescents in achieving long-term social health.

6

General Discussion

GENERAL DISCUSSION

6.1 Overview

Despite the growing body of research on the dynamics of emotions and emotion regulation, most studies have focused on the dynamics of intensity (e.g., T. Sun et al., 2025; see review by Reitsema et al., 2022). Little is known about how types of emotions and regulation strategies change together over time, or how these type-related dynamics shape short-term emotion intensity and long-term well-being. Lack of clarity about these type-related dynamics in young people (i.e., adolescents and young adults) is especially problematic, given that dynamics of emotions and emotion regulation in adolescence and young adulthood may have long-term consequences in their social and mental health (Aldao et al., 2016; Hollenstein et al., 2004; McLaughlin et al., 2011; Preece et al., 2021; Silvers, 2022; Van der Giessen et al., 2015).

This dissertation fills these gaps. In this dissertation, I introduced a methodological approach from ecology (Bray-Curtis dissimilarity; Baselga, 2013b) that—after translation to emotion research—measures two type-related dynamics: strategy switching in emotion regulation and transitions between negative emotions. Following this, I showed how type-related dynamics in emotions and emotion regulation may reveal overlooked patterns with important consequent effects on short-term emotion outcomes and long-term social and mental health in young people.

This chapter starts with a summary of findings. Afterward, I reflect on the findings, acknowledge the limitations of my studies, give suggestions to address the limitations, and outline viable future directions of research. Furthermore, I discuss the implications of the current findings to young people and to clinicians, before concluding this dissertation.

6.2 Summary of Findings

Emotion regulation variability entails two processes: endorsement change, referring to overall initiation or inhibition of emotion regulation, and strategy switching, referring to changing from one type of strategy to another (Aldao et al., 2015). In Chapter 2, through simulation studies, I found that Bray-Curtis dissimilarity is a suitable method to measure emotion regulation variability and its two constituent processes, endorsement change and strategy switching. Applying Bray-Curtis dissimilarity to three real-world datasets, I found that greater switching between emotion regulation strategies is robustly related to subsequently lower levels of negative emotion intensity within young adults. This indicated that switching between emotion regulation strategies may be beneficial in attaining a low intensity of negative emotions.

Before emotion regulation strategies come into play, another process, emotion differentiation, is thought to take place. Emotion differentiation, defined as how well is one labelling their emotions and measured by the distinctiveness of intensities of emotions, is thought to help one regulate their negative emotions (Erbas et al., 2021; Kashdan et al., 2015). In Chapter 3, however, I found the opposite: Young people with temporarily heightened emotion differentiation have subsequently lower emotion regulation variability and feel worse (i.e., higher negative and lower positive emotions). This indicates that moments where one knows better what one feels are followed by more stable emotion regulation strategy use (lower emotion regulation variability). In reverse, higher emotion regulation variability is followed by less emotion differentiation. This indicates that after young people change their emotion regulation strategy use, they know their emotions less well at the next moment. Both heightened differentiation and regulation variability preceded contra-hedonic outcomes, which referred to increased negative emotions and decreased positive emotions. This indicated that there can be discomfort, in terms of feeling worse emotionally, after heightened emotion differentiation or emotion regulation variability. How this finding on the relation between emotion regulation variability and subsequent emotion intensity may appear to conflict with the results in Chapter 2 will be examined further in Section 6.5.3.

Type-related dynamics can occur within a single moment, as in emotion differentiation, or across moments, as in emotion transitions. Emotion transitions describe how emotions change from one type to another over time. Even if a transition is between negative emotions (e.g., from anger to sadness), it may support emotion regulation by enhancing clarity and action readiness, compared to staying stuck in one emotion (Hollenstein et al., 2013; Singh et al., 2021). In Chapter 4, I found that transitions between negative emotions were significantly associated with reductions in overall negative emotion intensity. Moreover, such reductions were larger among young adults with higher depressive symptoms. This indicated that negative emotion transitions may have immediate benefits in decreasing intensity of negative emotions, especially for young adults with depressive symptoms.

These chapters (Chapter 2 to 4) explored short-term emotion outcomes subsequent to different emotion (regulation) dynamics, but emotion dynamics may also shape long-term changes in social and mental health. Loneliness and depressive symptoms are theorized to influence each at both short- and long-term timescales (Cacioppo & Cacioppo, 2018). Within timescales, I found that there is a reinforcing feedback loop between loneliness and depressive symptoms, both short-term (1.5-hourly) and long-term (half-yearly). In other words, once loneliness or depressive symptoms were heightened, the other tended to increase in turn after 1.5 hours or half a year. Additionally, I found that short-term dynamics between loneliness and depressed feelings shape long-term changes in loneliness: Adolescents who felt more depressed 1.5 hours after heightened loneliness showed smaller half-yearly increases in trait loneliness. However, this buffering effect was not predicted by the hourly depressed-to-loneliness relation, nor did either hourly relation predict half-yearly changes in depressive symptoms. In sum, findings in Chapter

5 suggest that feeling depressed shortly after loneliness can be a normative process that protects adolescents from having long-term loneliness.

Overall, all chapters contributed to the overarching aim of this dissertation, which is to show that type-related dynamics in emotion and emotion regulation can precede or accompany short-term emotion outcomes (Chapter 2, 3, 4, 5) and long-term outcomes in social health (Chapter 5). Importantly, these type-related dynamics predicted the outcomes above and beyond the intensity of emotion and emotion regulation (Chapter 3, 4, 5). In other words, additional information beyond intensity dynamics can be extracted by applying type-related dynamics indices on the same data. My dissertation also established the reliability of applying Bray-Curtis dissimilarity on ESM data through simulation studies (Chapter 2). Building on that, I showcased the feasibility of applying Bray-Curtis dissimilarity on emotion to capture emotion transitions (Chapter 4) and emotion regulation to capture emotion regulation variability (Chapter 2, 3) across ESM studies with different designs. I wrote an R tutorial on applying Bray-Curtis dissimilarity on ESM (Lo, 2023), which has been applied in recent work (Zhu et al., 2025), indicating its potential to be further applied in research that analyzes ESM data.

6.3 Theoretical Implications

In this dissertation, I clarified and extended multiple theories related to emotion (regulation) dynamics. First, I introduced Bray-Curtis dissimilarity as an index of emotion regulation variability. This index, theory-aligned with Aldao et al. (2015)'s model on emotion regulation variability and flexibility, separates and quantifies two key processes: endorsement change and strategy switching. I showed that both processes independently predicted subsequent short-term emotion intensity outcomes. Depending on which covariates are controlled for, emotion regulation variability is differently related to emotion outcomes (Chapter 2 and 3). This suggests what emotion regulation variability means can be sensitive to the conditions at which it takes place. These findings contribute to the growing view that effective emotion regulation is not just about which strategy one uses. Instead, having variability is crucial to adjust strategies according to contextual demands (Aldao et al., 2015; Troy et al., 2013).

Second, I tested Kashdan et al. (2015)'s model, which proposes that emotion differentiation (knowing one's emotions) helps regulate emotions. My results in Chapter 3 suggest a more nuanced picture. Specifically, a temporal pattern opposite to the theoretical prediction emerged: greater emotion regulation variability was followed by decreases in emotion differentiation. While further work is needed to understand the underlying mechanisms, these results suggest that theoretical models about emotions and their regulation, like Kashdan et al. (2015)'s, should incorporate bidirectional influences between emotions and their regulation. Moreover, heightened emotion differentiation (a) preceded more stable (but not more variable) strategy use and (b) was directly associated with feeling worse subsequently (higher negative and lower positive emotion intensity) but not indirectly via emotion regulation variability. Together, these findings suggest that within short timeframes (1.5–3 hours), differentiation does not improve emotion intensity outcomes. A possible revision to Kashdan et al. (2015)'s model is to distinguish between short-term and long-term effects: differentiation may bring short-term discomfort, with benefits unfolding only over longer timescales. This refinement brings the model closer in structure to the Evolutionary Theory of Loneliness (ETL; tested in Chapter 5), which distinguishes between short-term and long-term processes (Cacioppo & Cacioppo, 2018).

In testing the within-timescale relations between loneliness and depressive symptoms, I found that heightened depressed feelings are followed by increases in loneliness an hour later (Chapter 5). This contrasts with the ETL's prediction that depressed feelings may reduce loneliness in the short term through preventing initiation of new social interactions and attracting solace from supportive others (Allen & Badcock, 2003; Balsters et al., 2013; Cacioppo & Cacioppo, 2018). A possible implication for the ETL is that these theorized social mechanisms unfold more slowly, suggesting that reductions in loneliness following depressive states may require days or even weeks to materialize.

Finally, in Chapters 4 and 5, I set aside regulation and treated emotions as a system. Grounded in the dynamic systems perspective, I analyzed the dynamics between emotions to assess the state and function of the emotional system. Even when limited to negative emotions (Chapter 4) or the pair of loneliness and depressed feelings (Chapter 5), hourly type-related dynamics predicted short-term intensity changes in these emotions. This extends the use of the dynamic systems perspective by analytical approaches that preserve continuous intensity information, without reducing emotions to categorical or binary states. Further, the interconnection between timescales, also expected from the dynamic systems perspective (Granic, 2005; Jordan, 2013), was supported: short-term coupling from loneliness to depressed feelings buffered adolescents against long-term increases in loneliness. These results suggest that applying general principles of dynamic systems perspective is especially fruitful with joint consideration of domain-specific theories like the ETL.

6.4 Developmental Implications: Dynamics of Emotion and Emotion Regulation in the Developmental Periods of Adolescence and Young Adulthood

This dissertation examined emotion regulation dynamics in young people. I expected that type-related dynamics would relate to short- and long-term emotion outcomes during adolescence and young adulthood, which are periods of developmental change marked by emotional challenges and developmental opportunities (Bailen et al., 2019; Grosse & Streubel, 2024; Nook et al., 2018; 2020; Reitsema et al., 2022; Zimmermann & Iwanski, 2014). This expectation was supported in short-term findings (Chapters 2 to 5), many of which were cross-validated across multiple datasets (Chapters 2 to 4). Long-term findings (Chapter 5) further showed that adolescents with stronger hourly coupling from loneliness to depressed feelings were buffered against rising loneliness across six months.

It is plausible that age-related factors influenced the emotion (regulation) dynamics observed in this dissertation. In Chapter 3, I analyzed five datasets, each covering an age range from early adolescence to young adulthood (ages 11 to 25). Across datasets, younger adolescents reported higher positive and lower negative emotions, while older participants showed the reverse. These observations were consistent with previously reported age trends (Bailen et al., 2019; Griffith et al., 2021; Reitsema et al., 2022). These trends support the interpretation that some differences between datasets may reflect age-related variation. However, this interpretation should be made cautiously, as study design differences likely also contributed to between-dataset variability. Against this background, two trends from dataset-specific descriptive statistics and model estimates are worth noting. First, strategy switching was less common among early adolescents and more common in late adolescence and early adulthood. This suggested that strategy switching as a form of variability might be less common in younger adolescents and develop with age. Second, the reciprocal hindrance between emotion differentiation and regulation variability was most pronounced in older groups. This was especially true for the association between emotion differentiation and strategy switching. These two trends—and the extent to which they are related—can inform interesting future research questions about how type-related emotion and emotion regulation dynamics evolve across development.

6.5 Methodological Implications

6.5.1 On Theory-Index Alignment

Throughout this dissertation, I have examined four type-related dynamics of emotion and emotion regulation: emotion regulation variability, emotion differentiation, emotion transition, and pairwise coupling between loneliness and depressed feelings. One strength of this dissertation is demonstrated by the theory-index alignment in all chapters.

Theory-index alignment is what I refer to as how well a dynamic index aligns with the processes proposed by theory; it can be considered a miniature version of the theory-analysis alignment that theorists and methodologists have called for (Hamaker, 2023; Hopwood et al., 2022). In this dissertation, I demonstrated an improvement in theory-index alignment in Chapter 2. There, I argued that using standard deviation to measure emotion regulation variability fails to capture how one strategy changes in relation to others. I introduced Bray-Curtis dissimilarity as an alternative, which better reflects two theorized processes: changes in endorsement and switching across strategies. Although

Bray-Curtis dissimilarity has been applied in two more chapters (testing whether emotion differentiation helps emotion regulation, Chapter 3; capturing emotion transitions, Chapter 4), this does not mean it suits all theories and research questions, such as the ETL discussed in Chapter 5. The ETL posits that loneliness triggers depressive responses, but it does not imply that loneliness must decline as depressed feelings rise. That was why in Chapter 5, I used cross-lagged coupling but not Bray-Curtis dissimilarity to model the theorized temporal link in a way that is close to the ETL.

6.5.2 On Considering Which Variables to Include When Deriving Type-Related Dynamics

Not just the selection of indices, but deciding how many types of emotion or types of emotion regulation to include in the study should also begin with theory. Some theories are specific. In Chapter 5, I focused only on loneliness and depressed feelings because the ETL predicted mutual influence between these two (Cacioppo & Cacioppo, 2018). At other times, theories may not have specified which emotions to include, for example the theories guiding emotion regulation variability, emotion differentiation, or emotion transitions (Aldao et al., 2015; Erbas et al., 2014; Hollenstein, 2015; Hollenstein et al., 2013; Kashdan et al., 2015).

Including too few variables may lead to unreliable index estimates (see leave-one-emotion-out sensitivity analyses in Chapter 4). However, researchers must balance their quest of reliability with participant burden, which is both an ethical concern and affects data quality and compliance (Eisele et al., 2022). Instead of trying to be exhaustive, one approach is to include items from established theoretical frameworks, for example referencing the PANAS scales and core affect model (Russell, 2003; Watson et al., 1988) as exemplified in Chapter 2 and 4 and other studies (e.g., Kochhar et al., 2025). An additional strategy is the idiographic approach. Letting participants generate or co-construct their own emotion or strategy lists can increase personal relevance and reduce redundancy (Olthof et al., 2023). A benefit of using dynamic indices such as regulation variability, differentiation, or transition is their readiness in adapting to whatever set of emotions that is available. As shown in Chapters 2 through 4, these indices function across varying item sets and contexts.

6.5.3 On Model Selection: For Forecasting the Outcome or For Evaluating an Index?

Chapters 2 and 3 in this dissertation present a case of nested models and a problem on model selection. Chapter 2 showed that greater emotion regulation variability predicted lower subsequent negative emotion intensity. Yet, the Chapter 3 model, which can be considered as a more complex version of the Chapter 2 model, gave seemingly opposite results. After including covariates such as the intensity of emotion regulation strategy deployment, emotion regulation variability predicted worse emotional outcomes (increases in negative and decreases in positive emotions). Which model should we use, and is emotion regulation variability beneficial or harmful in the short-term?

The inconsistency arises from the dependency between emotion regulation variability and its covariates in the more complex model in Chapter 3. In concrete terms, emotion regulation variability, as calculated by Bray-Curtis dissimilarity, is nonlinearly dependent on the mean intensity of strategy use, because mean intensity is part of the denominator in the formula that calculates Bray-Curtis dissimilarity (structurally dependent; Aiken et al., 1991; Marquardt, 1980; McClelland et al., 2017). When there is dependency between predictors and covariates, their estimates are less reliable and less stable (Morrow-Howell, 1994; Salmerón-Gómez et al., 2025; Smith & Sasaki, 1979). Big changes in estimates are possible from small differences in samples used for analysis. This explains the opposite signs of estimates of models from Chapter 2 and 3, which are based on different datasets. Statistical adjustments are possible for linear dependency in single-level regression, but are unavailable for non-linear dependency in the current temporal multilevel analytical context (Iacobucci et al., 2016; Shieh, 2011; Yaremych & Preacher, 2024).

If prediction is our only goal, the exact direction of any single predictor matters less, because all predictors work collectively in producing the forecasted emotion outcomes. Dependency between predictors and covariates generally does not compromise overall model prediction (Kroll & Song, 2013; Morrissey & Ruxton, 2018). Whether the simpler model in Chapter 2 or the more complex model in Chapter 3 should be selected depends on which has a better model fit. In principle, for forecasting, a researcher is free to further add any additional indices as long as the model fit improves without overfitting (Hofman et al., 2021; Yarkoni & Westfall, 2017).

However, the considerations are different if we aim to determine whether a certain type-related dynamic, say emotion regulation variability, is good or bad for the sake of guiding behavioral change in individuals for the short-term emotion outcomes, i.e., in a causal sense. The nonlinear dependency between emotion regulation variability and the mean intensity of regulation strategies complicates this goal, because if one of them is changed, the other is going to nonlinearly change. This complication resembles the over-control bias, which describes the scenario where researchers include covariates that are causally implicated by predictors and lead to biased estimation and interpretation of the predictor (Rohrer, 2018). To avoid complicating interpretation, results from the simpler model in Chapter 2 may be more informative. Free from dependencies, it offers clearer insight into whether promoting emotion regulation variability could improve short-term outcomes. As such, considering the theoretical and implementational implications in model selection (Deisenhofer et al., 2024; Evans, 2019), the model from Chapter 2 is a better candidate for generating hypotheses in future intervention research to determine whether emotion regulation variability is beneficial or harmful.

6.6 Limitations and Suggestions for Future Research

This dissertation has several limitations that should be acknowledged. These include the absence of contextual information, the assumption that ESM self-reports capture emotional experience, and the uncertainty surrounding what occurs in the intervals between ESM observations. I first elaborate on each of these limitations and then outline potential ways future research may address them.

First, contexts in daily life are a part of the theoretical underpinning of all research questions in this dissertation; for example, in Chapter 2, the expectation that emotion regulation variability might affect short-term emotion intensity outcomes was based on the assumption that variability enables flexibility when contexts changed. However, as with many experience sampling (ESM) studies, a key limitation of our analyses is the lack of contextual information. Without knowing the contexts in which participants reported their emotions or emotion regulation, we cannot determine at which contexts do our findings apply most strongly (Kuppens et al., 2022; Mestdagh & Dejonckheere, 2021). Put it another way, the results reflect average effects across daily life, but in which specific contexts they are strongest remains unclear.

Second, an assumption I have made in all chapters is that ESM self-reports reflect the actual emotional experience the participants are having. One possible critique of this assumption is that the dynamics of self-reported emotions may instead reflect a change in the emotion label of the same experience, i.e., a process of finding words to describe the experience. Little is known about the point at which ESM assessments lie on this experience-labeling continuum, although early work that compared self-reports of emotions in ESM versus laboratory conditions has suggested the self-reported ratings (partially) reflect emotional experience (Barrett, 2004).

Third, another limitation of this dissertation lies in the uncertainty about what happens between assessments; we rely on adjacent ESM snapshots, which cannot represent the continuous flow of people's emotional processes (Hollenstein, 2021). Recent studies found that daily-life negative emotion episodes last for a median of 1 to 2 hours (De Calheiros Velozo et al., 2023; Li, Vaessen, et al., 2024; Schreuder et al., 2024). Given that most ESM assessments in this dissertation were spaced 1.5 hours apart, we can infer that about half of the longer emotion-eliciting events were likely captured. While this means the other half was missed, these shorter-lived negative emotion episodes may be less relevant for understanding difficulties in emotion regulation. Difficulties in emotion regulation often center around emotion episodes that are harder to regulate and take longer to resolve, rather than those that spontaneously recover. In fact, some studies focus specifically on these more intense or enduring events, for example by assessing emotion and event details about the most negative event each day (e.g., Olthof et al., 2024).

6.6.1 *Suggestions for Approaching Context: Measure It, Build It, or Leave It Behind*

Here, I outline three broad approaches: to measure context, to build context into the study, and to abandon context. To measure contexts, there are multiple options, such as restricting measurement to theory-specific types of contexts (e.g., measure social context in follow-up studies of Chapter 5 about loneliness, Hemberg et al., 2022; Qualter et al., 2015; Van Roekel et al., 2015), including a broad range of contexts using situation characteristics frameworks (e.g., DIAMONDS, which encompasses characteristics like duty, intellect, adversity, etc.; Horstmann et al., 2021; Rauthmann et al., 2014), adopting an idiographic approach by allowing participants to construct their own questionnaire supplemented by their definitions (Schiepek, Eckert, et al., 2016; Schiepek, Stöger-Schmidinger, et al., 2016; van den Bergh et al., 2024) or to describe their context freely through open text or audio recordings at each observation (von Klipstein et al., 2025), and passively monitoring physical activity (Hoemann et al., 2020), location (Saragosa-Harris et al., 2022), background noise level (Coolen et al., 2024), crowdedness (Stieger & Lewetz, 2024), social interactions (Elmer et al., 2019), etc. In preparing the measured contexts for analysis, researchers can choose to treat context as dynamic rather than static. Rather than identifying which context is related to emotion outcomes, researchers can focus on the variability of (types of) contexts, and examine whether the variability of context and emotion (regulation) dynamics synchronize (Kalokerinos & Koval, 2024) to derive flexibility from variability.

To build context into the study design itself, researchers can adopt quasi-experimental study designs. One example is to collect data around common significant events (e.g., exam results release; Dejonckheere et al., 2021). Another example is to conduct the study among a closed system of participants who are in the same ecological context, e.g., meditation retreats or weekend trips (e.g., Elmer & Stadtfeld, 2020). Building context into the study design standardizes context across participants, allows clearer interpretation of context-specific dynamics, and gives a higher signal-to-noise ratio, which translates to greater statistical power in addressing the research questions (Dejonckheere et al., 2020).

The last approach, which is a radical one, is to not measure context at all. From a strong interpretation of Frijda's definition, emotions have already embedded context through appraisals, bodily cues, and readiness for action (Barrett et al., 2025; Frijda, 2016). For example, a student having an upcoming exam may remain anxious in a park in the morning and at home in the afternoon, because the experienced future-exam-laden context remains unchanged. Conversely, another student who also has an upcoming exam may transition from one emotion to another even though the student stays in the same observed context (e.g., at home), perhaps due to emotion regulation attempts such as relaxation. In other words, contexts as experienced can diverge from those as observed. A person's emotions are signals about their experiential state as synthesized from external and internal inputs, including contexts (Barrett et al., 2025).

The "Emotion Stimulus Critique", although made for experimental emotion research, can prompt researchers to rethink how to approach context (Pascual-Leone, Herpertz, et al., 2016). Instead of focusing on standardizing experimental stimuli, which can elicit different emotional responses in types and intensity across participants, researchers may gain more insight by referencing to participants' subjective experience. The same can be said about contexts; it might be more beneficial to center the analyses on emotions. This is because the context-emotion link is highly individualized (Beck & Jackson, 2022), plausibly exhibiting greater individual differences than the experimental stimuli-emotion link. In ESM studies, emotions are typically self-reported and are centered within each participant before analysis. Daily life emotion research with ESM can be said to have already come close to the kind of emotion research envisioned by the critique, namely standardizing around participants' emotional experience, true to their lives.

6.6.2 Suggestions for Evaluating the Assumption of the Self-Report-Experience Link

There are two avenues to test my assumption that ESM self-reports reflect—at least to a certain extent—actual emotional experience. One possible avenue is to qualitatively study participants' response process (Schorrlepp et al., 2025) by asking how participants arrive at their self-reports, although this may prove challenging for younger participants (dos Santos Kawata et al., 2021; Mankus et al., 2016). Another possible avenue that does not require introspection is to make use of multimodal assessments of emotions to corroborate the self-reports of participants (Hoemann et al., 2023). For example, changes in self-reported emotions, if accompanied by changes in physiology (e.g., changes in cardiac activity without physical movements, Hoemann et al., 2020), voices (Karapanos, 2020; J. Sun et al., 2020; Weidman et al., 2020), or facial expressions (as captured by cameras on smartphones, bicycles, or cars; Dollack et al., 2022; Kosch et al., 2020; Liu et al., 2021), can be seen as ascertaining the link between self-reports and experience.

6.6.3 Suggestions for Addressing Gaps Between ESM Observations

To fill the gaps between ESM observations, three promising approaches can be considered. One is the event-contingent burst design, which adds a brief sequence of high-frequency assessments immediately after participants report an unpleasant event (e.g., four burst assessments 10 minutes apart, Schreuder et al., 2024). This design allows for more accurate modeling of emotional change during critical moments. The second is the use of innovative assessment tools such as continuous affect drawing. In this approach, participants draw a line between two anchors of the previously and currently reported emotion levels to reconstruct the trajectory of change between two ESM assessments. Initial validation suggests that it offers an average information gain of 7 points on a scale of 100 (Cloos et al., 2025), which is substantial when compared to the descriptive statistics of data analyzed in this dissertation (e.g., negative emotion intensity M[SD] = 15[12] points on a scale of 100, Chapter 3). The third is to make use of deep learning algorithms to recover a flow of probabilistic states of emotions (Angkasirisan, 2025). This can be done by integrating a sufficient amount of ESM emotion self-reports, continuous multimodal assessments, and continuous passive contextual data, which might be possible with the advancements in data collection technology and increased interdisciplinary collaboration. In principle, all three approaches can similarly be used to enrich the understanding of context between ESM observations. Overall, these approaches may help future research more accurately capture emotion dynamics in greater temporal granularity.

6.7 Future Research Directions

6.7.1 Clarifying Developmental Change in Type-Related Emotion (Regulation) Dynamics

To extend the tentative age-related findings from Chapter 3, future research should clarify how type-related dynamics of emotion and emotion regulation change across development. Several avenues can be considered. First, cross-sectional designs using datasets that span adolescence to young adulthood could reveal age-related patterns (e.g., a temporary dip in emotion differentiation during mid-adolescence, Nook et al., 2018).

Second, researchers can pool multiple datasets to widen the coverage of the age range and enhance statistical power to explore age trends, as exemplified in Chapter 3. Combining datasets mitigates possible cohort effects in the first approach, but introduces the risk of confounding due to study design differences. This risk can be mitigated in two ways: by incorporating a larger number of datasets and by applying multiverse analysis. With broader dataset coverage, each age group can be represented by multiple sources, thereby reducing the influence of any single study's design. Multiverse analysis involves testing whether age-related trends are robust across a range of study design-related analytic decisions, such as timescales, exclusion criteria, and variables used to derive dynamic indices (Steegen et al., 2016). Together, these strategies can help assess and account for design-related variability, increasing confidence in findings on age trends.

Third, measurement burst designs can be considered, which refer to repeating ESM data collection for multiple short periods longitudinally, e.g., 5 years apart (Carstensen et al., 2011). By following the same young people from adolescence into adulthood, researchers can examine within-person changes over time and draw stronger conclusions about developmental trajectories in emotion and regulation dynamics.

6.7.2 Positive Emotions and Positive Emotion Regulation

A key future direction for research on type-related emotion dynamics is to include positive emotions more fully. In this dissertation, positive emotions were only partially examined in Chapter 3 on positive emotion differentiation. Positive emotion regulation variability and transitions between positive emotions were not examined. However, the theoretical underpinning of strategy-context fit and the argument that variability is necessary for flexible systems are equally applicable to positive emotion regulation (e.g., savoring, Quoidbach et al., 2010) and positive emotions. Positive emotions are suggested to play a role in facilitating emotion regulation (Gloria & Steinhardt, 2016). Furthermore, variability in average positive-emotion intensity and its relation with negative emotions across time are found to closely relate to mental health (Coifman et al., 2012; Gruber et al., 2013; Rafaeli et al., 2007; Zautra et al., 2000, 2005). Therefore, future studies could assess whether positive emotion transitions and positive emotion regulation variability precede desirable short-term or long-term outcomes.

This dissertation did not study type-related dynamics between positive and negative emotions (and emotion regulation). This was a result of two challenges: limited data availability and methodological constraints. For example, datasets in Chapter 2 centered on negative emotions and their regulation strategies, but did not measure positive emotion regulation strategies. Moreover, current implementations of dynamic indices cannot yet disaggregate type changes between categories, for example, emotion transitions by valence. When Bray-Curtis dissimilarity is applied to a set of positive and negative emotions, it cannot distinguish between transitions within negative emotions (e.g., sad to angry), within positive emotions (e.g., calm to excited), or across valence (e.g., angry to content). The same limitation applies to regulation strategies. To maintain interpretability, I restricted analyses to within-valence sets of emotions and regulation strategies.

Therefore, studying how type-related dynamics work in different categories of variables is an important future direction. In the study of negative emotion differentiation, emotions are seen as falling under different categories within the same valence. For example, anger and irritation belong to the same category, but anger and sadness do not. Individuals with higher within-category and integral (i.e., considering all emotions) negative emotion differentiation have higher self-esteem and lower levels of depressive symptoms (Erbas et al., 2019). A similarly category-sensitive approach might be adopted in advancing Bray-Curtis dissimilarity to handle across-category changes. When this advancement is realized, it will be possible to study whether transitions between positive and negative emotions are related to momentary antecedents (e.g., stressful events, Dejonckheere et al., 2021) and outcomes (e.g., emotion intensity). Together, such studies would provide a fuller picture of how positive and negative emotional processes jointly shape well-being.

6.7.3 Embracing Evolving Methodological Practices

Methodology for analyzing intensive longitudinal data is advancing rapidly, and several developments have emerged during the course of this dissertation. While not exhaustive, a few key methodological innovations should be considered when replicating or extending the present work. These include (i) the number of time points used to construct dynamic indices, (ii) modeling nonlinear effects, and (iii) addressing potential floor and ceiling effects in outcome variables.

First, this dissertation relied on two common approaches to compute moment-level dynamic indices: comparing adjacent time points and comparing one time point to all other observations within a person (Lichtwarck-Aschoff et al., 2009). Recent developments suggest promising alternatives, such as sliding-window approaches, which use a moving subset of time points (e.g., 15 time points, Dejonckheere et al., 2021) or all available time points before data collection is finished (Schat et al., 2024). Using these approaches to compute emotion regulation variability and emotion transitions further enables comparing observations in chunks, for example, using two observations as a unit for comparison (Baselga, 2013a). However, approaches that use more time points introduce a trade-off. Although covering more time points may make indices more informative, indices may become less modifiable in the real world. For example, attempting to switch strategies from one moment to the next is more intuitive than doing so based on the evaluation of many time points.

Second, this dissertation tested hypotheses under the assumption of linear relations between dynamic indices and outcomes, which can be considered an oversimplification. However, the link between emotion regulation variability and emotion intensity may follow a quadratic pattern, implying an optimal level of variability rather than a linear (e.g., "higher is better") interpretation (Hollenstein et al., 2013; Maciejewski et al., 2025). Other forms of nonlinearity, such as asymmetric dynamics, may also apply. Asymmetric dynamics refers to a different statistical relation when the outcome variable is above or below a threshold (Schaaf et al., 2025). For example, if applied to extend the findings in Chapter 3, emotion differentiation might relate to subsequent changes in emotion intensity differently when emotion intensity is above a person's mean intensity than when it is not. Future research should explore modeling such patterns using quadratic terms or asymmetric dynamics estimation methods.

6.7.4 Further Application and Development of Bray-Curtis Dissimilarity in Psychology

Although Bray-Curtis dissimilarity has been used in ecological research for decades, its application in psychological science is still in the early stages. In this dissertation, I used Bray-Curtis dissimilarity to examine emotion and emotion regulation, demonstrating that it can effectively capture emotion transitions and emotion regulation variability. Building on my work, some recent studies have extended the use of Bray-Curtis dissimilarity to domains such as personality and parenting (Hoffenaar & Lo, 2025; C. J. Lee & Beck, 2025), suggesting its broader relevance to psychological processes. As more studies adopt this method, its utility in revealing meaningful type-related dynamics will become clearer.

Bray-Curtis dissimilarity can be made more useful for psychological science with three steps of methodological clarification. First, we need a clearer understanding of how Bray-Curtis dissimilarity behaves when the variables it is derived from approach the bounds of their scales, for example, when multiple emotions are rated at or near zero. Similar work has been done on more conventional indices, for example, the standard deviation has a smaller possible range when the observations it derives on are close to the lower or upper bounds (Mestdagh et al., 2018). Knowing the numerical behaviours of Bray-Curtis dissimilarity under these conditions will help us better interpreting it. Second, it would be valuable to develop post hoc techniques that assess the relative contribution of each constituent variable to the overall dissimilarity. This would help identify which specific constituent variables (e.g., sadness or anger) are most or least involved in a given variability. Third, Bray-Curtis dissimilarity and multivariate approaches should be systematically compared using simulated and real-world data. Approaches covered in this dissertation can be considered, such as cross-lagged effects (Chapter 5) and emotion differentiation (Chapter 3), as well as methods beyond this dissertation, such as multilevel hidden Markov models (Aarts et al., 2025; Mildiner Moraga et al., 2024). The comparisons can clarify Bray-Curtis dissimilarity's relative strengths and opportunities in complementing other multivariate approaches, for example in quantifying the dissimilarity between states identified by multilevel hidden Markov models. Altogether, Bray-Curtis dissimilarity may become more useful in psychological science to capture dynamic, type-related change processes that may otherwise go unnoticed in traditional approaches.

6.7.5 Research on How to Stimulate Type-Related Dynamics in Emotions and Emotion Regulation

If emotion (regulation) dynamics were piano music, this dissertation has advanced our music appreciation in that not only changes in loudness (intensity) but also changes in keys (types) are crucial for the melody. However, this dissertation has not advanced the techniques for playing different keys, i.e., how to stimulate type-related dynamics. Therefore, a key future research direction is to identify what stimulates the type-related dynamics examined in this dissertation, including emotion regulation variability, emotion differentiation, emotion transitions, and the temporal coupling between loneliness and depressed feelings.

Recent work has started to explore emotion differentiation as an intervention target. These studies have highlighted several potentially active ingredients. Notably, many of these ingredients have also been mentioned in interventions for improving emotion regulation and reducing loneliness (Eccles & Qualter, 2021; Ellard et al., 2023). This overlap suggests that such ingredients may influence the emotion (regulation) system as a whole, rather than acting on isolated type-related dynamics. Accordingly, I outline these ingredients in general terms, without assigning each to a specific form of type-related dynamics. Potentially active ingredients include (a) deepening knowledge of the characteristics of types of emotions (Vedernikova et al., 2021) and when particular emotion regulation strategies are most effective (Cohen Ben Simon et al., 2022; Fincham et al., 2023; Ortner et al., 2016; J. Zaki & Williams, 2013); (b) broadening vocabulary/repertoire, such as learning new emotion words (Matt et al., 2024) and emotion regulation strategies (De France & Hollenstein, 2017; Wright et al., 2024); (c) using scaffolding approaches, such as moving from offering predefined emotion words for young people to rate in an ESM study to offering free responses (Seah & Coifman, 2024); and (d) cultivating self-monitoring and awareness in both emotion and emotion regulation (Guendelman et al., 2025; Berking et al., 2008; Sheppes et al., 2014). Moreover, because the same repeated-measures emotion data can be used to derive different forms of type-related dynamics (emotion differentiation, emotion transitions, and coupling between a pair of emotions), researchers can examine which of these dynamics an intervention most strongly influences. Qualitative follow-ups, such as interviews (Verity et al., 2024), could further identify which components of the intervention are most effective in eliciting these dynamics.

In addition, it may be fruitful to examine emotion regulation strategies' effects on emotion transitions. Although emotion transitions have rarely been the explicit focus of emotion regulation studies, they are implied in many emotion regulation strategies. For example, relaxation may elicit calmness and simultaneously decrease anxiety, and reappraisal may accompany increases in hope (Peh et al., 2017). In daily life, reappraisal and distraction have been shown to precede increases in positive emotions (Boemo et al., 2022). Therefore, a viable direction is to examine whether specific strategies consistently elicit particular patterns of transitions. Another possible direction concerns the timing of emotion regulation strategy deployment and how strategies are sequenced (Kalokerinos et al., 2017), which may facilitate desirable changes in emotion type and intensity.

6.8 Practical Implications for Young People and Clinicians

Although further research is warranted to replicate our results with other samples, we may already start considering the practical implications in a few ways.

Following our overarching aim, the main implication of this dissertation is the need to go beyond intensity and consider type in the dynamics of emotion and emotion regulation. Emotional life is like playing a piano—what matters is not just changes in loudness (intensity), but movement between the keys (types of emotion or emotion regulation strategies). An awareness of type-related dynamics informs us about how we might respond to negative emotional experience differently. In moments when young people struggle with regulating their emotions, instead of saying, "Let's try harder", we might ask, "Is there another way to engage with these emotions?" Rather than focusing only on reducing the intensity of negative emotions, we might ask, "Are there other emotions to arrive at?" These questions reflect processes highlighted in this dissertation, namely, switching between emotion regulation strategies (Chapter 2) and transitioning between negative emotions (Chapter 4). These type-related dynamics may ultimately pave the way toward reduced negative emotion intensity. Such questions can be asked by young people themselves, or by those around them, including peers, partners, parents, or mentors. Importantly, these questions are not meant to dismiss existing efforts. Instead, they invite young people to clarify their emotional experience and to regulate their emotions flexibly depending on how the situation unfolds (Aldao et al., 2015; Berking et al., 2008; Birk & Bonanno, 2016).

Type-related dynamics do not always bring immediate relief. For example, heightened emotion differentiation may feel uncomfortable in the short term, possibly because it requires deeper attention to unpleasant emotions or uses up cognitive resources (Chapter 3). However, adolescents with higher differentiation on average tend to report lower negative emotions and higher positive emotions (Chapter 3). Short-term discomfort, and in fact short-term experience of negative emotions, might not be so bad after all: adolescents who have stronger short-term coupling from loneliness to depressed feelings may feel worse in the short term but are less likely to experience long-term increases in loneliness (Chapter 5). Even if it is a negative emotion that young adults transition into, transitions can bring immediate relief from negative emotion intensity (Chapter 4). Taken together, we need to rethink our natural tendency to avoid negative emotions and the instinct to reduce them (S. C. Hayes et al., 1996; Higgins, 1997). Temporary emotional discomfort can be part of an adaptive process as we deal with the changing world. Hence, an implication is that before regulating them, we should simply allow negative emotions in the first place, as they are there for informative and functional reasons (Ford et al., 2018; Greenberg, 2006; Lench et al., 2015; Schwarz & Clore, 1983).

The findings in this dissertation have potential implications for clinicians. First, type-related dynamics such as emotion regulation variability and emotion transitions can enhance how clinicians interpret clients' homework (e.g., mood diaries Kazantzis et al., 2010) and other monitoring tools already used in therapy (Bos et al., 2022; Lichtwarck-Aschoff et al., 2023). In ecology, dynamics between multiple species can forecast future state transitions in ecology (e.g., from a vegetated to a barren land) (Dakos, 2018; O'Brien et al., 2023). Among these dynamics between species, compensatory changes, in which one species replace another, are key to understanding an ecosystem's resilience against state transitions (Bai et al., 2004; Choi et al., 2004; Doncaster et al., 2016; J. Wang et al., 2023). The corresponding type-related dynamics discussed in this dissertation, emotion transitions and emotion regulation variability, may therefore hold potential for clinical psychology in predicting onset of or recovery from psychopathology (Helmich et al., 2024). Type-related variability, such as switching between emotion regulation strategies or transitioning between negative emotions, may provide clinicians and researchers with richer information about clients' risk (e.g., absence of variability, indicating inflexibility) and progress (e.g., variability accompanied with symptom reduction) from the same amount of emotion (regulation) data collected. Second, clinicians can observe type-related dynamics during sessions and, when these dynamics appear adaptive, help clients transfer them into daily life (Kazantzis et al., 2010; Ryum et al., 2023). This includes guiding clients to reflect on which specific dynamics were helpful, under what conditions they occurred, and how they unfolded. For instance, in the supportive environment of therapy, a client may be able to focus on a negative emotion and, through that process, uncover another underlying negative emotion that requires attention. If this emotion transition proved beneficial, the therapist can work with the client to identify ways to recreate similar supportive conditions in everyday settings (e.g., specific safe spaces or people) so that helpful emotional transitions can happen outside of therapy as well.

These clinical implications might be readily integrated into the care routine by clinicians who are emotion-focused in their therapeutic approach. However, clinicians working within other therapeutic frameworks may also find utility for these ideas, as many approaches recognize that changes in emotion are inevitable in clients' progress (Fosha, 2005; Gülüm & Soygüt, 2022; A. M. Hayes, 2015; Lynch et al., 2006; Tesarz et al., 2019). The clinical implications presented here are not meant to be prescriptive but rather to serve as additional tools that clinicians can flexibly draw upon when working within the time and contextual constraints of real-world practice.

6.9 Concluding Remarks

This dissertation highlights that our emotional lives unfold not only through changes in intensity but also in type. Type-related dynamics, including switching between emotion regulation strategies, differentiating emotional experiences, transitioning between negative emotions, and the coupling between loneliness to depressive symptoms, offer a richer understanding of young people's emotional lives. In the sensitive developmental periods of adolescence and young adulthood, these patterns are not merely descriptive, but are linked to young people's short-term emotion intensity outcomes and long-term social health. While more research is needed to determine whether these dynamics can be systematically leveraged in interventions, this dissertation already offers evidence for young people, researchers, and clinicians to rethink how emotions change and how emotions can be changed. Much like music is defined not just by loudness but also by the dynamics between playing different keys, we must understand our emotion and emotion regulation beyond their intensity but the type-related dynamics between emotions and between the ways we regulate them. Attuning to type-related emotion dynamics may be key to understanding, and eventually guiding, the melodies of our emotional lives.

Appendix A

Supplemental Materials for Chapter 2 (A Theory-Informed Emotion Regulation Variability Index: Bray–Curtis Dissimilarity)

SUPPLEMENTARY MATERIAL 1: ALTERNATIVE EMOTION REGULATION VARIABILITY INDICES: CHOICE OF INDICES AND COMPARISON APPROACHES

There are two sections in this Supplemental Material. First, we introduce three additional dissimilarity indices suitable for emotion regulation (ER) experience sampling method (ESM) data (Legendre & Legendre, 2012), and *SD* of successive differences, a possible *SD*-based index suggested by an anonymous reviewer. Second, we introduce all-moment comparison as an alternative approach to successive difference in comparing moments to calculate dissimilarity indices are calculated by comparing moments.

Other Indices To Estimate ER Variability

Table S1.1 presents Jaccard dissimilarity, chord distance and chi-squared distance as other dissimilarity indices that might be useful to estimate ER variability. These indices are suitable for ER ESM data (p. 324, Legendre & Legendre, 2012), which are commonly multivariate and measured using ordinal scale. In addition to three dissimilarity indices. We also present variants of *SD*-based indices, namely between-strategy *SD* successive difference and *SD* of successive differences. For convenience of comparison, we also repeated the formulae and example calculations of Bray-Curtis dissimilarity.

Jaccard dissimilarity can be partitioned into replacement and nestedness subcomponents (Baselga, 2013b), but partitioning is not available for the other dissimilarity indices presented here. Jaccard dissimilarity is standardized and range from 0 to 1; chord distance is standardized and range from 0 to 1.44 (square root of 2); chi-squared distance is not a standardized dissimilarity index and has a lower bound at 0 but no upper bound.

Table S1.1

Formulae of Different Dissimilarity Indices with Exemplified Calculation Steps

	Formula	Calculating dissimilarity for Time 3 of Table S1.2 (j = Time 3; k = Time 2; distraction and social sharing as two ER strategies)
Intermediate Steps		
A (Shared ratings across x_j and x_k)	$\sum_{i=1}^{N_{ER}} min(x_{ij}, x_{ik})$	$MIN(8{,}5) + MIN(0{,}2) = 5 + 0 = 5$
B (Exclusive ratings of x_j)	$\sum_{i=1}^{N_{ER}} x_{ij} - A$	$(5+2) - 5 = 2$
C (Exclusive ratings of x_k)	$\sum_{i=1}^{N_{ER}} x_{ik} - A$	$(8+0) - 5 = 3$
Bray-Curtis Dissimilarity		
Full index	$\sum_{i=1}^{N} \frac{\lvert x_{ij}-x_{ik}\rvert}{x_{ij}+x_{ik}} \equiv \frac{B+C}{2A+B+C}$	$\frac{2+3}{2\times5+2+3} = \frac{5}{15} = 0.333$
Replacement	$\frac{min(B,C)}{A+min(B,C)}$	$\frac{MIN(2,3)}{5+MIN(2,3)} = \frac{2}{5+2} = 0.286$
Nestedness	$\frac{\lvert B-C\rvert}{2A+B+C} \times \frac{A}{A+min(B,C)}$	$\frac{\lvert 2-3\rvert}{2\times5+2+3} \times \frac{5}{5+MIN(2,3)} = \frac{1}{15} \times \frac{5}{7} = 0.048$
Jaccard Dissimilarity		
Full index	$\frac{B+C}{A+B+C}$	$\frac{2+3}{5+2+3} = \frac{5}{10} = 0.500$
Replacement	$\frac{2min(B,C)}{A+2min(B,C)}$	$\frac{2MIN(2,3)}{5+2MIN(2,3)} = \frac{2\times2}{5+2\times2} = 0.444$
Nestedness	$\frac{\lvert B-C\rvert}{A+B+C} \times \frac{A}{A+2min(B,C)}$	$\frac{\lvert 2-3\rvert}{5+2+3} \times \frac{5}{5+2MIN(2,3)} = \frac{1}{10} \times \frac{5}{9} = 0.055$
Other indices		
Chord Distance	$\sqrt{\sum_{i=1}^{N_{ER}} \left(\frac{x_{ij}}{\sqrt{\sum_{i=1}^{N_{ER}} x_{ij}^2}} - \frac{x_{ik}}{\sqrt{\sum_{i=1}^{N_{ER}} x_{ik}^2}} \right)^2}$	$\sqrt{\left(\frac{5}{\sqrt{(5^2+2^2)}} - \frac{8}{\sqrt{(8^2+0^2)}}\right)^2 + \left(\frac{2}{\sqrt{(5^2+2^2)}} - \frac{0}{\sqrt{(8^2+0^2)}}\right)^2}$ $= \sqrt{\left(\frac{5}{\sqrt{(29)}} - \frac{8}{\sqrt{(64)}}\right)^2 + \left(\frac{2}{\sqrt{(29)}} - \frac{0}{\sqrt{(64)}}\right)^2} = 0.378$

Table S1.1

Formulae of Different Dissimilarity Indices with Exemplified Calculation Steps (*continued*)

	Formula	Calculating dissimilarity for Time 3 of Table S1.2 (j = Time 3; k = Time 2; distraction and social sharing as two ER strategies)
Chi-squared Distance	$\sqrt{\sum_{i=1}^{N_{ER}}\sum_{t=1}^{n}x_{it}}\sqrt{\sum_{i=1}^{N_{ER}}\frac{1}{\sum_{t=1}^{n}x_{it}}\left(\frac{x_{ij}}{\sum_{i=1}^{N_{ER}}x_{ij}}-\frac{x_{ik}}{\sum_{i=1}^{N_{ER}}x_{ik}}\right)^2}$	$\sum_{i=1}^{N_{ER}}\sum_{t=1}^{n}x_{it}=\sqrt{(1+8+5+3+3+0)+(0+0+2+0+0+3)}=\sqrt{25}$ $\sum_{t=1}^{n}x_{(distraction)t}=1+8+5+3+3+0=20$ $\sum_{t=1}^{n}x_{(social\ sharing)t}=0+0+2+0+0+3=5$ Chi-squared Distance $=\sqrt{25}\sqrt{\left(\frac{1}{20}\right)\left(\frac{5}{5+2}-\frac{8}{8+0}\right)^2+\left(\frac{1}{5}\right)\left(\frac{2}{5+2}-\frac{0}{8+0}\right)^2}=0.714$
Between-strategy standard deviation successive difference	$\sqrt{\frac{\sum_{i=1}^{N_{ER}}\left(x_{ij}-\bar{x}_j\right)^2}{N-1}}-\sqrt{\frac{\sum_{i=1}^{N_{ER}}\left(x_{ik}-\bar{x}_k\right)^2}{N-1}}$	$\frac{(5-3.5)^2+(2-3.5)^2}{2-1}-\frac{(8-0)^2+(4-0)^2}{2-1}=2.121-5.657=-3.536$
Standard deviation of successive differences	$\sqrt{\frac{\sum_{i=1}^{N_{ER}}\left(\left(x_{ij}-x_{ik}\right)-\left(\bar{x}_j-\bar{x}_k\right)\right)^2}{N-1}}$	$\frac{((5-8)-(3.5-4))^2+((2-0)-(3.5-4))^2}{2-1}=(-2.5)^2+(2.5)^2=12.5$

Note. x is a set of all reported scores of ER strategies use across all measurement occasions within a person. x_{it} refers to a specific score of the ith ER strategy (out of a total of N_{ER} strategies) of the t^{th} moment among the total number of observations n. $\bar{x}_t$ refers to the mean of all scores of the tth moment. Moments j and k are the moments of interest which the dissimilarity indices are concerned with; A, B, and C are intermediate steps commonly seen in ecology literature to compute Bray-Curtis dissimilarity and Jaccard dissimilarity (e.g., MacGregor-Fors et al., 2022).

All-Moment Comparison as an Alternative Comparison Approach

To facilitate our discussion[1], we annotate $d_{(j,k)}$ as a generic notation for any index listed in Table S1.1 that compares two moments j and k.

Recap on Successive Difference

In the main text, ER variability indices were calculated in successive difference. Successive difference focuses on the temporal order of ER (Kalokerinos et al., 2017) by inspecting how a moment of interest is different from the previous moment. In formula, dissimilarity in successive difference (d_{suc}) of a moment j is given by $d_{(j,k)}$ by substituting *k* with the previous moment *j* – 1:

$$d_{suc(j)} = d_{(j,j-1)}$$

Like the examples mentioned in the main text, Time 5 (see Table S1.2) has exactly similar ratings as the previous moment, so it is expected to have no variability in successive difference. Time 3, in contrast, was different from the previous moment in both distraction and social sharing. As such, Time 3 is expected to have variability in successive difference.

All-moment Comparison

An alternative to the successive difference approach is an all-moment comparison, which operationalizes ER variability as the uniqueness of that moment among all other moments. Under the all-moment comparison approach, variability is given by the mean of comparisons between the moment of interest and all other moments to show how much one particular moment deviates from the person's usual pattern of ER. In formula, dissimilarity in all-moment comparison (d_{amm}) of a moment j is expressed as follows:

$$d_{amm(j)} = \frac{1}{n-1} \sum_{t=1}^{n} d_{(j,t)}$$

Such within-person deviations have been seen as valuable datapoints that invite explanations (McGuire, 1997): It may indicate synchronization to contextual demands (Aldao et al., 2015), exploration and experimentation of alternatives (Stamkou et al., 2018), or failing to maintain stable deployment of ER strategies (inability to show consistent performance; MacDonald et al., 2009).

Edmund's example from the main text is repeated here to show examples of Bray-Curtis dissimilarity calculated in both comparison approaches (Table S1.2). Time 6 is a unique moment in which Edmund rated 0 in distraction but 3 in social sharing, which is quite different from all other time points (as reflected by strategy mean of 2.83 and 0.83 respectively). Comparatively, Time 3, though also with rating 2 in social sharing, is a less

1 We do not discuss all-moment comparisons for the *SD* of successive differences, as they are by definition only calculated as successive differences.

unique moment because the rating 5 for distraction is closer to ratings of distraction at other moments. The higher uniqueness in Time 6 than Time 3 is reflected by the higher Bray-Curtis dissimilarity in all-moment comparison.

Table S1.2

Bray-Curtis Dissimilarity in Successive Difference and All-Moment Comparison Calculated from Artificial Data (Example 'Edmund') as Discussed in the Main Text

			Successive Difference			**All-moment Comparison**		
Time Point	Distraction	Social Sharing	Bray-Curtis Dissimilarity	Replacement	Nestedness	Bray-Curtis Dissimilarity	Replacement	Nestedness
1	1	0	-	-	-	0.71	0.20	0.51
2	8	0	0.78	0.00	0.78	0.60	0.26	0.35
3	5	2	0.33	0.29	0.05	0.50	0.12	0.37
4	3	0	0.40	0.00	0.40	0.47	0.20	0.27
5	3	0	0.00	0.00	0.00	0.47	0.20	0.27
6	0	3	1.00	1.00	0.00	0.92	0.87	0.05

Note. No Bray-Curtis dissimilarity or its subcomponents in successive difference were calculated for Time Point 1 because there is no previous time point.

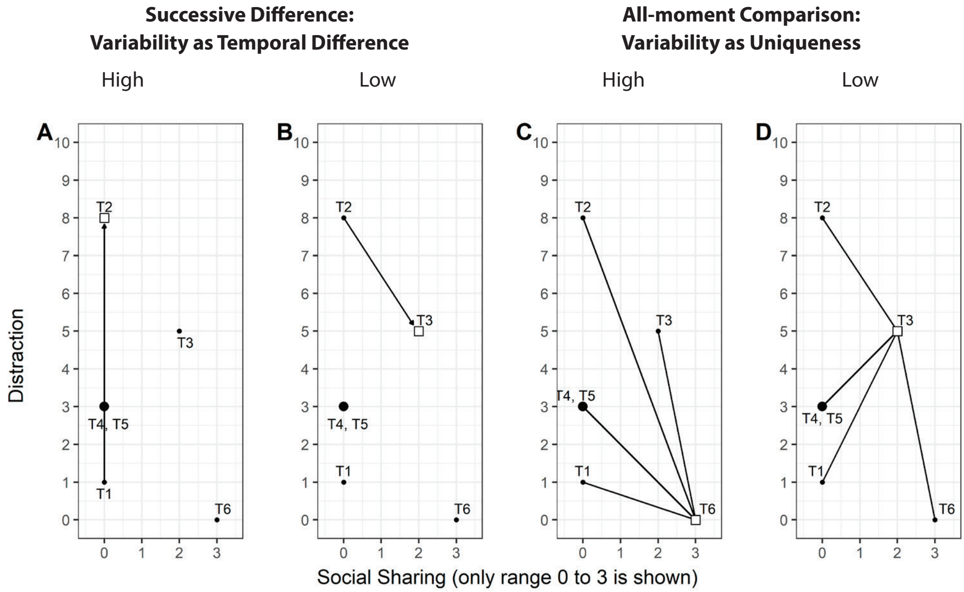
Graphical Illustration of the Two Approaches

Figure S1A and S1B illustrate the successive comparison approach, with Time 2 and Time 3 as the moments of interest respectively. Graphically, the line that starts at the previous moment and ends at the moment of interest represents the successive difference. The line that points to Time 2 (Figure S1A) is longer than the line that points to Time 3 (Figure S1B), which reflects higher successive difference at Time 2 compared to Time 3.

Figure S1C and S1D illustrate the all-moment comparison approach, with Time 6 and Time 3 as the moments of interest respectively. Graphically, the lines that radiate from the moment of interest to all other time points represent comparisons between the moment of interest and all other moments. The lines are visibly longer in Figure S1C than those in Figure S1D, which reflect higher uniqueness of Time 6, the moment of interest in Figure S1C.

Figure S1

Two Approaches of Temporal Comparisons Visualized with Data from Table S1.2



Note. The four panels share the same x- and y-axes labels. The range of x-axes is truncated to 0 – 3 to save space but x- and y-axes share the same range from 0 – 10. Time points 1 to 6 are indexed T1 to T6. T4 and T5, which fall on the same position, is represented by a larger dot. White squares are the moment of interest in the panels. Panel A: T2, a moment with relatively high successive difference. Panel B: T3, a moment with relatively low successive difference. Panel C: All-moment comparisons of T6, a time point with relatively high uniqueness. Panel D: All-moment comparisons of T3, a time point with relatively low uniqueness.

SUPPLEMENTAL MATERIAL 2: SETUP OF SIMULATION 1: VAR(1) MODEL

We chose different values for five parameters, namely a within-strategy autocorrelation parameter ∈ (-0.09, 0.12, 0.33), a within-strategy standard deviation parameter ∈ (0.10, 0.19, 0.28), a between-strategy correlation parameter ∈ (-0.11, 0.18, 0.47), the number of ER strategies ∈ (2, 3, 5, 6) and the number of observations per participant ∈ (30, 70, 100). Numbers inside the ∈ () brackets are distinct choices of parameter values. Values of the autocorrelation, within-strategy SD, and between-strategy correlation parameters were chosen as one SD below the mean, the mean, and one SD above the mean of VAR(1) parameter estimates of two reference datasets (Blanke et al., 2020; Verhagen et al., 2022). Values of the number of ER strategies and the number of observations per participants parameters were chosen with reference to the same two reference datasets and study designs commonly seen in other ESM studies.

The values of five parameters were cross-tabulated to give 3 x 3 x 3 x 4 x 3 = 324 unique profiles. Each profile has a unique combination of values chosen for the five parameters. Table S2.1 shows sample profiles that result from cross-tabulation of five parameters.

Table S2.1

Sample Profiles that Result from Cross-Tabulation of Parameters.

	Parameter values				
Profile number	ρ_{auto}	σ	ρ_{cor}	N_{ER}	n
1	-0.09	0.10	-0.11	2	30
2	0.12	0.10	-0.11	2	30
3	0.33	0.10	-0.11	2	30
4	-0.09	0.19	-0.11	2	30
5	0.12	0.19	-0.11	2	30
6	0.33	0.19	-0.11	2	30
…	…	…	…	…	…
324	0.33	0.28	0.47	7	100

Note. ρ_{auto}: autocorrelation; σ: within-strategy *SD*; ρ_{cor}: correlation between strategies; N_{ER}: number of ER strategies; n: number of observations.

The VAR.sim function in tsDyn package allows researchers to simulate VAR models by providing coefficients (Narzo et al., 2009). We ran VAR.sim on each of the 324 profiles for 1000 times to get 324000 simulated datasets. There are five key input arguments for VAR.sim: B (matrix of coefficients), n (number of observations to simulate), lag (number of lags of the VAR to simulate), include (type of deterministic regressor, such as a linear or cyclic time trend), innov (innovations used for in the VAR to simulate; by default multivariate normal), and varcov (variance-covariance matrix for the innovations). We specified the input as listed in Table S2.2.

Table S2.2

Input for VAR.sim in Data Simulation.

VAR.sim argument	Input (number of rows in matrix is from N_{ER} profiles)
B	A square matrix with diagonal value as ρ_{auto}, Example: when $\rho_{auto} = 0.12$, $\begin{matrix} 0.12 & 0.00 \\ 0.00 & 0.12 \end{matrix}$.
n	Value *n* from cross-tabulated profiles.
lag	Value 1, which is the default value of VAR.sim
include	String "none", as we did not simulate deterministic trends.
innov	Multivariate normal, which is the default of VAR.sim
varcov	A square matrix constructed in two steps. First, set diagonal value as 1 and off-diagonal value as ρ_{cor}. Second, multiply the whole matrix by σ^2, Example: when $\sigma = 0.28$ and $\rho_{cor} = 0.47$, varcov = $\begin{matrix} 0.08 & 0.04 \\ 0.04 & 0.08 \end{matrix}$.

The datasets generated by VAR.sim have a grand mean of 0 by default; values generated can thus be positive or negative. To enable calculation of dissimilarity indices, which can only handle positive values, we linearly transformed the multivariate time series generated by adding a constant ("3") to ensure that all values were positive. An example dataset generated with parameter values of profile 1 as listed in Table S2.1 is shown at Table S2.3.

Table S2.3

An Example Simulated Dataset out of 324000 Datasets generated in Simulation 1

	Emotion Regulation Strategy	
Observation	1	2
1	3.075	3.042
2	2.948	2.917
3	2.952	3.108
4	2.992	2.939
5	3.070	3.066
6	2.815	3.051
7	2.947	2.928
8	2.820	3.190
9	2.822	2.853
…	…	…
30	3.002	3.204

SUPPLEMENTAL MATERIAL 3: SETUP OF SIMULATION 2: RESAMPLING THE LORENZ SYSTEM

The Lorenz system is a system of differential equations. Initially published to study an atmospheric condition called the rolling fluid convection, the differential equations have three key system coefficients: σ, the ratio of fluid viscosity to thermal conductivity, β, aspect ratio of the space studied, and ρ, temperature difference between the top and bottom of the system. We used the lorenz function in *nonlinearTseries* package (Garcia, 2022) to generate solutions for the Lorenz system. The default values in the lorenz function in system coefficients are $\sigma = 10$, $\beta = 8/3$, $\rho = 28$, and initial coordinates at $x = -13$, $y = -14$, and $z = 47$. With these input, Lorenz system becomes symmetrical with its solutions of points in three-dimensional coordinates looking like a two-winged butterfly (Figure S3; Strogatz, 2018). Due to its symmetrical property, we can easily identify to which wing a point belongs. The coordinates of the three axes represent the levels of intensity of the three ER strategies in our simulation, and points represent possible observations.

We transformed the Lorenz System in two ways before using it for simulation data generation: First, we flipped the signs the values of the y-axis (i.e., negative values become positive, and vice versa) so that the two wings have the same mean across coordinates. Second, we linearly transformed coordinates in all three axes for all points so that their mean values were at 50. By flipping the signs of values of the y-axis, the grand mean of all coordinates in each wing became the same. This enabled introducing strategy switching without systematically influencing endorsement change (i.e., the mean intensity of strategies). This is because given large number of resampling, the overall intensity of endorsing ER strategies will be the same regardless of which wing the points of observations are sampled from. By linear transformation, all coordinates became positive, which was necessary for calculation of dissimilarity indices that could only handle positive values. The manipulations are illustrated by Panel B in Figure S3: if signs were not flipped, grand means of coordinates in points in one wing would be systematically larger than the other.

Values of z are not impacted by switching, as shown in Figure S3C and Figure S3D; they have almost the same distributions whichever wing they are sampled from. They are nevertheless included in the analysis because there may be strategies in an individual's ER repertoire that are not involved in the switching process.

We chose different values for three parameters, namely probability of the switching parameter ∈ (.10, .30, .50, .70, .90), number of ER strategies ∈ (3, 6, 9) and number of observations per participant ∈ (30, 70, 100). The values of five parameters were cross-tabulated to give 5 x 3 x 3 = 45 profiles. Each profile has a unique combination of values chosen for the five parameters. Table S3.1 shows sample profiles that result from cross-tabulation of three parameters.

Table S3.1

Sample Profiles that Result from Cross-Tabulation of Parameters.

	Parameter values		
Profile number	Probability of switching	Number of ER strategies	Number of observations per participant
1	0.10	3	30
2	0.30	3	30
3	0.50	3	30
4	0.70	3	30
5	0.90	3	30
6	0.10	6	30
…	…	…	…
45	0.90	9	100

In the first moment of each time series dataset, we sampled a point in the Lorenz System and used its coordinates as the ratings of ER strategies. Each following moment had a specified probability of switching to be sampled from a different wing until specified number of observations were generated in the dataset. We ran these procedures on each of the 45 profiles for 1000 times to get 45000 simulated datasets. In Table S3.2, we present two example simulated datasets generated with parameter values of profile 1 (low probability of switching) and profile 5 (high probability of switching) listed earlier in Table S3.1.

Table S3.2

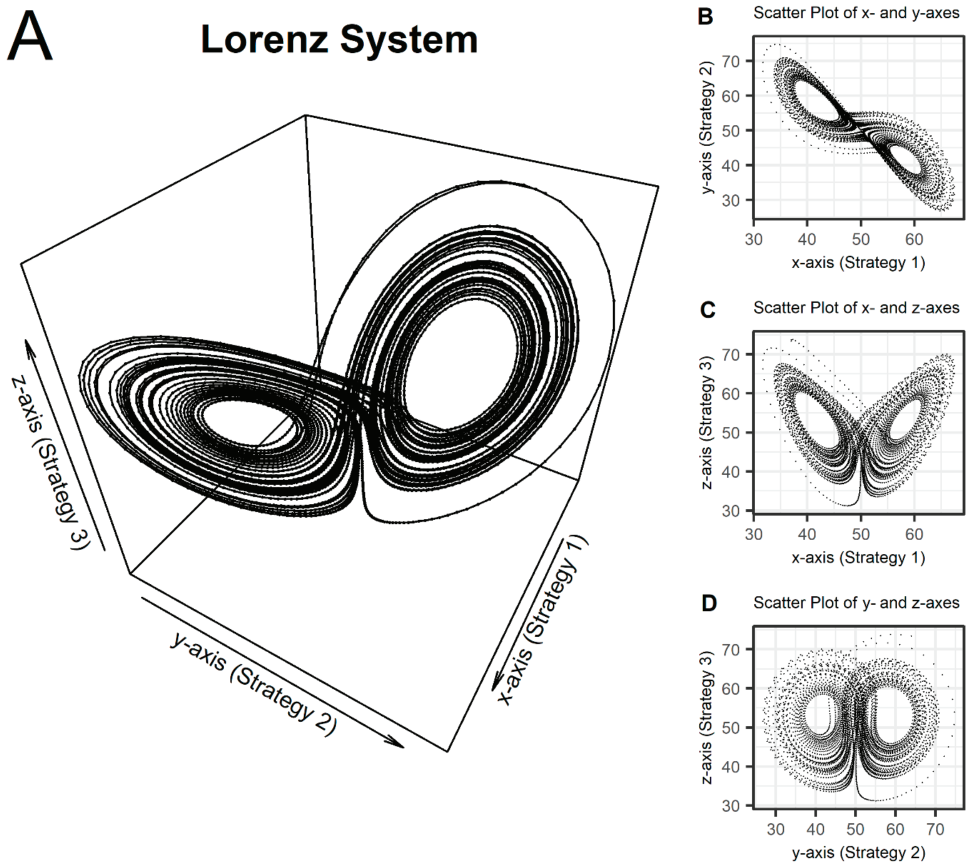
Two Simulated Datasets with Different Probability of Switching out of 45000 Datasets Generated in Simulation 2

	Profile 1 (from Table S3.1) **Probability of switching = 0.1** **Number of ER strategies = 3** **Number of observations = 30**				**Profile 5 (from Table S3.1)** **Probability of switching = 0.9** **Number of ER strategies = 3** **Number of observations = 30**			
Observation (Point)	Strategy(Coordinate)			Switching?	Strategy(Coordinate)			Switching?
	1(x)	2(y)	3(z)		1(x)	2(y)	3(z)	
1	63.3	58.1	64.5	-	53.6	48.2	55.5	-
2	58.4	62.6	46.2	Yes	46.4	45.5	45.6	No
3	52.4	53.8	40.6	No	54.5	58.7	34.3	Yes
…	…	…	…	…	…	…	…	…
25	54.8	58.1	40.3	No	50.6	51.0	38.0	No
26	53.8	56.4	40.8	No	41.1	36.8	47.1	Yes
27	49.2	46.2	50.6	Yes	51.9	53.2	44.1	Yes
28	43.2	39.9	45.1	No	44.7	41.8	43.2	Yes
29	49.8	49.7	35.7	No	50.1	50.5	42.0	Yes
30	49.6	45.5	52.5	No	49.9	49.7	35.9	Yes

Note. Switching is noted when there is a change in order of whether x or y are larger in two successive observations. An example of no switching would be comparing, in observations 25 and 26 of Profile 1, where values of x are smaller than values of y in both cases, indicating that there is no switching. An example of switching would be comparing observations 25 and 26 from profile 5, where values of x are smaller that values of y in observation 25, but values of x are larger than y in observation 26, indicating that switching in order took place.

Figure S3

Scatter Plots of the Lorenz System



Note. Panel A: Scatter plot of the Lorenz System in a three-dimensional space. Panel B to D: Scatter plots of two of the three axes of the Lorenz System. In this Lorenz System, the y-axis has been flipped ($y' = -y$) so that the same grand mean is found in each wing. Additionally, all three axes are linearly transformed so their mean values are 50. This is to enable calculation of dissimilarity indices, which can only handle positive values.

SUPPLEMENTAL MATERIAL 4: COMPLETE SIMULATION AND REANALYSIS RESULTS

This supplementary material first presents simulation results for dissimilarity indices that were not discussed in the main text, namely *SD* of successive differences, Jaccard dissimilarity, chord distance, and chi-squared distance. Then, we present simulation results for an alternative temporal comparison approach (all-moment comparison approach) that are described in Supplemental Material 1. We conclude this supplemental material with recommendations on which dissimilarity index is best suitable to estimate ER variability.

Sensitivity of Additional Indices in Successive Difference to Simulation Parameters

In addition to Bray-Curtis dissimilarity and *SD*-based indices discussed in the main text, we examine the performance of four additional indices: *SD* of successive differences in each strategy, Jaccard dissimilarity, chord distance, and chi-squared distance. *SD* of successive differences is a variant to the *SD*-based indices presented in the main analyses. Jaccard dissimilarity, chord distance, and chi-squared distance are alternative dissimilarity indices for assessing variability in biodiversity data that are similarly structured as ER experience sampling method data (Legendre & Legendre, 2012). Calculation steps of these indices can be found in Supplemental Material 1.

To examine how sensitive each index was to each simulation parameter, we calculated partial correlation (Table S4.1) and correlation results (Table S4.2) between dataset-level means of indices and all simulation parameters. In other words, we used the same approach as in the main analyses. In the following discussion, we focused on interpreting partial correlation results, because partial correlation can reflect the association between an index and a parameter after adjusting the index's relationship with other parameters. This allows easier interpretation of an index's performance.

As in the main analyses, we examined the association with four main parameters (i.e., autocorrelation, within-strategy SD, between-strategy correlation, and probability of switching) and two design parameters (i.e., number of ER strategies, and number of observations). In the main analyses reported in the manuscript, we found Bray-Curtis dissimilarity in successive difference to have good sensitivity to all simulation parameters. Other indices had several limitations. For example, between-strategy *SD* was negatively associated with between-strategy correlation, and within-strategy *SD* lacked the components to distinguish how strategy switching and endorsement change processes are affected by the correlation between ER strategies. The additional analyses can be benchmarked against these results. Any indices showing stronger associations with simulation parameters in the expected directions can be seen as outperforming Bray-Curtis dissimilarity.

SD of successive differences detected strategy switching. Like the replacement subcomponent of Bray-Curtis dissimilarity, it exhibited similar sensitivity towards the switching probability parameter from Simulation 2. However, it had weaker negative correlation with autocorrelation. Additionally, it showed an undesirable positive correlation with the between-strategy correlation parameter in Simulation 1 and the number of ER strategies in Simulation 1 and 2. Together, we conclude that *SD* of successive differences had undesirable properties in estimating ER variability.

Then, we compared alternative dissimilarity indices (i.e., Jaccard dissimilarity, chord distance, and chi-squared distance) with Bray-Curtis dissimilarity and *SD*-based indices (all calculated using successive difference). Jaccard dissimilarity had similar sensitivity towards all parameters as Bray-Curtis dissimilarity had, matching most of the theorized directions of associations with strategy switching and endorsement change. However, in Simulation 2 Jaccard dissimilarity nestedness subcomponent was negatively associated with the probability of switching parameter. There was no endorsement change systematically introduced in Simulation 2, so this negative association was undesired.

Chord distance and chi-squared distance were both able to detect strategy switching. Like the replacement subcomponent of Bray-Curtis dissimilarity, they exhibited similar sensitivity towards the switching probability parameter from Simulation 2. However, like between-strategy *SD*, both showed an undesirable positive correlation with the between-strategy correlation parameter and the number of ER strategies in Simulation 1. Together, this indicates that both chord distance and chi-squared distance shared undesirable properties in estimating ER variability.

To summarize, among all indices in successive differences evaluated, Bray-Curtis dissimilarity remained the index with the best performance in estimating ER variability in terms of strength of associations with simulation parameters.

Comparing the All-Moment and Successive Difference Temporal Comparison Approaches

Simulations Results for All Indices

In the main text, we inspected the sensitivity of indices calculated in successive difference and not the all-moment comparison approach. Here, we compared ER variability indices calculated in successive difference and ER variability indices calculated in all-moment comparison. In terms of the direction of association, all-moment comparison indices were the same as indices calculated in successive differences. The only exception was Jaccard dissimilarity: compared to Bray-Curtis dissimilarity, the Jaccard dissimilarity full index was more positively related to the number of ER strategies. This undesirable property makes

Jaccard dissimilarity larger when there are more ER strategies in the study. Overall, Bray-Curtis dissimilarity remained the most suitable index to estimate ER variability.

In terms of the strength of association, indices in all-moment comparison had weaker associations with autocorrelation and probability of switching than indices in successive differences. This is expected, given the autocorrelation and probability of switching parameters both influence a moment with reference to the previous moment, which is conceptually more in line with successive difference than with all-moment comparisons.

These results suggested that, all-moment comparison indices can detect varying levels of ER variability and the two constituent processes of strategy switching and endorsement change, though they show weaker sensitivity towards variability driven by autoregression or primary strategy switching. However, unlike the successive difference approach, the all-moment comparison can give information about the uniqueness of the moment of interest within a person.

Predictive Validity of Bray-Curtis Dissimilarity Calculated in All-Moment Comparison Approach

Similar to Part II of the main text, after showing that Bray-Curtis dissimilarity in all-moment comparison approach is sensitive to the hypothesized ER variability processes, we evaluated its predictive validity in empirical data. We compared the estimates of multilevel models predicted by Bray-Curtis dissimilarity in all-moment comparison approach against other models presented in the main text in associating with negative affect (NA) at both moment- and person-level (Table S4.3).

In terms of person-level associations, Bray-Curtis dissimilarity in all-moment comparison was consistently negatively associated with NA, consistent with results of the successive difference approach results. For person-level associations, Bray-Curtis dissimilarity in all-moment comparisons was significantly associated with lower NA, with one exception (Nestedness component in dataset 1). For moment-level associations, while being consistently negative, Bray-Curtis dissimilarity in all-moment comparison was not always *significantly* associated with lower NA in the subsequent moment. However, these weaker associations were understandable: the models were about moment-to-moment changes in NA, so a matching successive difference approach to comparison in calculating the index is likely to be more predictive. Importantly, Bray-Curtis dissimilarity remained more consistently associated with NA than the *SD*-based indices at both person-level and moment-level.

A lower root mean squared error (RMSE) of a model indicates higher predictive power. As shown in Table S4.4, mean RMSEs from subcomponent models of Bray-Curtis dissimilarity in all-moment comparison approach were consistently lower than RMSEs from *SD*-based models in all three datasets. RMSEs of Bray-Curtis dissimilarity subcomponent models were smaller when calculated in the all-moment approach than when calculated in the successive difference approach, though differences were small.

Overall, the predictive validity of Bray-Curtis dissimilarity calculated using the all-moment comparison approach was similar to that calculated using successive differences, and it was also better than SD-based indices.

Conclusion

We evaluated indices calculated in successive difference and all-moment comparison approaches. In both approaches, Bray-Curtis dissimilarity remained the index with the best performance in estimating ER variability in terms of strength of associations with simulation parameters. Researchers are advised to use Bray-Curtis dissimilarity regardless of the comparison approach they choose.

Bray-Curtis dissimilarity calculated in all-moment comparison had less sensitivity than when calculated in successive difference in detecting ER variability driven by autoregression or primary strategy switching. However, researchers who decide to inspect ER variability as uniqueness of a moment within a person may still want to use the all-moment comparison approach.

Table S4.1

Summary of Influences of Simulation Parameters on Two Processes of Emotion Regulation (ER) Variability and the Partial Correlations between Parameters and ER Variability Indices under Two Approaches of Temporal Comparisons

		Simulation 1 parameters					Simulation 2 parameters		
		ρ_{auto}	σ	ρ_{cor}	N_{ER}	n	p_{switch}	N_{ER}	n
ER variability process		Theorized or ideal directions of association							
Strategy switching		-	+	-	0	0	+	0	0
Endorsement change		-	+	+	0	0	0	0	0
ER variability index		Partial correlation							
Within-strategy *SD*		-.44	.98	.00	.00	.02	.19	.00	.07
Between-strategy *SD*		-.27	.96	-.82	.52	-.03	.02	.06	.00
*SD of s*uccessive differences		-.68	.93	-.20	.34	-.02	.74	.66	-.00
Successive difference	Between-strategy *SD*	-.24	.89	-.59	-.78	-.01	.02	-.89	.00
	Bray-Curtis dissimilarity	-.80	.97	.01	.00	-.03	.88	.01	-.01
	Replacement	-.41	.80	-.79	.64	-.01	.88	.66	.00
	Nestedness	-.52	.88	.74	-.58	-.02	.02	-.83	-.02
	Jaccard dissimilarity	-.80	.97	.00	.02	-.03	.88	.09	-.01
	Replacement	-.41	.80	-.80	.66	-.01	.88	.68	.00
	Nestedness	-.51	.88	.75	-.60	-.01	-.13	-.83	-.02
	Chord distance	-.67	.94	-.72	.73	-.02	.88	.63	.00
	Chi-squared distance	-.67	.94	-.72	.73	-.02	.87	.61	-.01
All-moment comparisons	Between-strategy *SD*	-.16	.90	-.63	-.81	-.01	.01	-.93	-.01
	Bray-Curtis dissimilarity	-.43	.98	.01	-.01	-.01	.21	.02	.04
	Replacement	-.13	.83	-.82	.68	.00	.20	.72	.05
	Nestedness	-.18	.90	.78	-.63	-.01	.00	-.87	-.03
	Jaccard dissimilarity	-.44	.98	-.01	.03	-.01	.21	.11	.04
	Replacement	-.13	.83	-.82	.69	.00	.19	.75	.05
	Nestedness	-.18	.90	.79	-.64	-.01	-.02	-.87	-.03
	Chord distance	-.18	.90	.79	-.64	-.01	.20	.70	.04
	Chi-squared distance	-.27	.95	-.76	.77	-.01	.19	.69	.03

Note. -: negative associations; +: positive associations; 0: no associations; ρ_{auto}: autocorrelation; σ: within-strategy *SD,* adjusted with a correction factor because the *SD* is inflated when autocorrelation is high (Beran, 1994); ρ_{cor}: correlation between strategies; N_{ER}: number of ER strategies; n: number of observations; p_{switch}: probability of switching.

Table S4.2

Summary of Influences of Simulation Parameters on Two Processes of Emotion Regulation (ER) Variability and the Correlations between Parameters and ER Variability Indices under Two Approaches of Temporal Comparisons

		Simulation 1 parameters					Simulation 2 parameters		
		ρ_{auto}	σ	ρ_{cor}	N_{ER}	*n*	p_{switch}	N_{ER}	*n*
ER variability process		Theorized or ideal directions of association							
Strategy switching		-	+	-	0	0	+	0	0
Endorsement change		-	+	+	0	0	0	0	0
ER variability index		Correlation							
Within-strategy *SD*		.04	.98	.00	.00	.01	.19	.00	.07
Between-strategy SD		.05	.89	-.34	.15	.00	.02	.06	.00
SD of successive differences		-.21	.87	-.07	.13	.00	.64	.51	-.00
Successive difference	Between-strategy *SD*	.00	.73	-.28	-.48	.00	.01	-.89	.00
	Bray-Curtis dissimilarity	-.19	.92	.00	.00	.00	.88	.01	.00
	Replacement	-.12	.56	-.57	.37	.00	.81	.39	.00
	Nestedness	-.15	.71	.44	-.28	.00	.01	-.83	-.01
	Jaccard dissimilarity	-.19	.92	.00	.01	.00	.88	.04	.00
	Replacement	-.12	.56	-.57	.37	.00	.80	.41	.00
	Nestedness	-.14	.70	.46	-.29	.00	-.07	-.83	-.01
	Chord distance	-.17	.79	-.31	.33	.00	.82	.36	.00
	Chi-squared distance	-.17	.79	-.31	.33	.00	.82	.35	.00
All-moment comparisons	Between-strategy *SD*	.04	.74	-.29	-.49	.00	.00	-.93	.00
	Bray-Curtis dissimilarity	.04	.98	.00	.00	.01	.21	.02	.03
	Replacement	.03	.60	-.58	.37	.00	.14	.71	.03
	Nestedness	.03	.76	.45	-.29	.00	.00	-.87	-.01
	Jaccard dissimilarity	.04	.98	.00	.01	.01	.21	.11	.04
	Replacement	.03	.59	-.58	.38	.00	.13	.74	.03
	Nestedness	.03	.74	.47	-.30	.00	-.01	-.87	-.02
	Chord distance	.03	.84	-.32	.33	.01	.14	.69	.03
	Chi-squared distance	.04	.84	-.32	.33	.01	.14	.68	.02

Note. -: negative associations; +: positive associations; 0: no associations; ρ_{auto}: autocorrelation; σ: within-strategy *SD,* adjusted with a correction factor because the *SD* is inflated when autocorrelation is high (Beran, 1994); ρ_{cor}: correlation between strategies; N_{ER}: number of ER strategies; *n*: number of observations; p_{switch}: probability of switching. In Simulation 1, chord distance could not be computed in 2 of the 324000 datasets simulated, so its coefficients were based on 323998 datasets.

Table S4.3

Multilevel Results on Moment-Level and Person-Level Components of Emotion Regulation (ER) Variability Indices in Predicting Negative Affect in Three Datasets

ER variability index		Moment-level results: Dataset 1	2	3	Person-level results: Dataset 1	2	3
Within-strategy *SD*		(no moment-level results)			-2.35** (0.79)	-0.59 (0.58)	-0.70* (0.27)
Between-strategy *SD*		-0.33* (0.13)	0.11 (0.08)	0.05 (0.06)	-3.44*** (0.54)	-0.25 (0.39)	-0.53** (0.17)
Between-strategy *SD* successive difference		-0.01 (0.12)	-0.08 (0.07)	0.15** (0.05)	0.28 (1.59)	-3.94** (1.32)	-1.49* (0.72)
Bray-Curtis dissimilarity	Successive difference	-0.44*** (0.12)	-0.18** (0.06)	-0.12** (0.04)	-1.58* (0.65)	-1.92*** (0.29)	-1.58*** (0.17)
Replacement	Successive difference	-0.41** (0.14)	-0.23** (0.08)	-0.13** (0.04)	-2.75* (1.23)	-1.77** (0.56)	-1.21*** (0.28)
Nestedness	Successive difference	-0.38* (0.16)	-0.08 (0.08)	-0.03 (0.04)	-1.71 (1.46)	-2.94** (1.09)	-3.11*** (0.51)
Bray-Curtis dissimilarity	All-moment comparison	-0.32 (0.26)	-0.45* (0.20)	-0.13 (0.11)	-1.99* (0.77)	-2.12*** (0.34)	-1.68*** (0.19)
Replacement	All-moment comparison	-0.30 (0.30)	-0.62** (0.22)	-0.33* (0.13)	-2.68* (1.06)	-2.05*** (0.45)	-1.49*** (0.23)
Nestedness	All-moment comparison	-0.50 (0.27)	-0.25 (0.21)	-0.10 (0.11)	-0.87 (1.64)	-2.00** (1.73)	-2.12*** (0.43)

Fixed effect (Standard error)

Note. Moment-level results are based on the within-person component, person-level results are based on the between-person component. Within-strategy and between-strategy *SD* were calculated with relative *SD* (Mestdagh et al., 2018). To calculate within-strategy *SD*, a person-level index, the mean *SD* across all strategies was used. Fixed effect and random effect of intercept and time factor, random effect of the variability indices, autoregressive error-structure, and covariances between intercept and slopes were estimated but are not displayed.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table S4.4

Means of Root Mean Squared Error (RMSE) of Multilevel Models of Emotion Regulation (ER) Variability Indices Predicting Negative Affect in Bootstrapped Samples from Three Datasets

	Unstandardized RMSE		
		Dataset	
ER variability index	1	2	3
Within-strategy *SD*	0.881	0.654	0.594
Between-strategy *SD*	0.846	0.635	0.577
Between-strategy *SD* successive difference	0.858	0.648	0.581
Successive difference approach			
Bray-Curtis dissimilarity (full index)	0.837	0.631	0.572
Bray-Curtis dissimilarity (subcomponents)	0.827	0.627	0.569
All-moment comparison approach			
Bray-Curtis dissimilarity (full index)	0.843	0.633	0.580
Bray-Curtis dissimilarity (subcomponents)	0.823	0.612	0.562

Note. We bootstrapped each dataset 1000 times to produce the above mean RMSEs. Within-strategy and between-strategy *SD* were calculated with relative *SD* (Mestdagh et al., 2018).

SUPPLEMENTAL MATERIAL 5: SENSITIVITY OF BRAY-CURTIS DISSIMILARITY IN DETECTING EMOTION REGULATION VARIABILITY UNDER DIFFERENT MEASUREMENT CONDITIONS

To check the robustness of applying Bray-Curtis dissimilarity to heterogeneous measurement conditions, we introduced two sets of conditions in varying levels of missingness and decimal places in rounding simulated data.

Missingness

Simulation 1 and 2 were conducted assuming there were no missing data. We repeated[2] Simulation 1 and 2 with five conditions of missingness: 10%, 20%, 30%, 40%, and 50%. We applied the "delete_MCAR" function from the missMethods package (Rockel, 2022) to simulate missing data at an observation level, akin to how participants in Experience Sampling Method (ESM) studies might miss some assessments. Table S5.1 reveals that as the missingness increased, Bray-Curtis dissimilarity remained sensitive towards the parameters, though the strength of some associations diminished from our original simulations without missing data. Ther largest decrease was noted at 50% missingness, where partial correlations between the full index and autocorrelation was decreased from r = -.80 (0% missingness) to r = -.63 (50% missingness).

Scale-mapping

In Simulations 1 and 2, we generated continuous data with many decimal places. However, in real-world ESM studies, researchers often make use of Likert-type scales, which commonly result in a loss of true variance due to scale-mapping. There are different degrees of loss of true variance depending on the scales applied researchers choose. For example, in a 11-point Likert scale, a true score of 1.222 may be rated as 1, where in a 100-point sliding scale, a true score of 12.22 (scaled up 10 times from 1.222) may be rated as 12. We repeated Simulation 1 and 2 with five conditions of scale-mapping with different levels of variance loss: we rounded generated data to 5, 4, 3, 2, and 1 decimal places. With fewer decimal places in rounding, the coarser the scale-mapping process is, and there is more loss of true variance. For example, a true score of 1.222 becomes 1.22 when rounded to 2 decimal places, and it becomes 1.2 when rounded to 1 decimal place. By rounding the generated continuous data, we aimed to at least partially reflect the difficulty in measurement in ESM researchers on assessing the true variance of ESM measures.

2 To keep computational costs reasonable in these 10 additional conditions, we ran Simulation 1 with 100 repetitions instead of the original 1000 repetitions. In measurement conditions closest to the original setup (i.e., with 10% missingness and 5 decimal places), the partial correlation coefficients were nearly identical to those obtained under the original conditions. This suggests that we can reliably interpret results based on 100 repetitions.

Our findings, detailed in Table S5.2, revealed that the loss of variance was due to mapping in measurement scales was negligible when rounding was applied. In other words, scale-mapping is expected not to critically affect the sensitivity of Bray-Curtis dissimilarity.

Table S5.1

Partial Correlations between Parameters and Bray-Curtis Dissimilarity Full Index and Subcomponents under Different Levels of Missingness

		Simulation parameters																							
		Autocorrelation						Within-strategy SD						Between-strategy correlation						Probability of Switching					
	Missingness (%)	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50	0	10	20	30	40	50
Successive Difference	Full Index	-.80	-.78	-.75	-.72	-.68	-.63	.97	.97	.96	.95	.94	.92	.01	.01	.02	.00	.01	.00	.88	.86	.84	.81	.77	.71
	Replacement subcomponent	-.41	-.39	-.38	-.36	-.34	-.32	.80	.79	.78	.76	.74	.70	-.79	-.78	-.77	-.75	-.72	-.69	.88	.86	.84	.81	.77	.71
	Nestedness subcomponent	-.52	-.51	-.48	-.46	-.42	-.39	.88	.87	.86	.84	.82	.78	.74	.73	.71	.68	.65	.60	.03	.03	.02	.02	.01	.01
All-moment Comparisons	Full Index	-.43	-.41	-.39	-.38	-.35	-.34	.98	.98	.98	.98	.97	.97	.01	.01	.02	.01	.01	.01	.21	.20	.19	.18	.16	.15
	Replacement subcomponent	-.13	-.12	-.13	-.13	-.12	-.12	.83	.82	.82	.82	.81	.80	-.82	-.82	-.81	-.81	-.80	-.79	.19	.19	.18	.17	.15	.14
	Nestedness subcomponent	-.18	-.18	-.17	-.17	-.16	-.16	.90	.90	.89	.89	.88	.87	.78	.77	.76	.76	.74	.73	.01	.01	.01	.00	.00	.01

Note. We also presented the original results (from Table 2.2) under 0% missingness for easy comparison.

Table S5.2

Partial Correlations between Parameters and Bray-Curtis Dissimilarity Full Index and Subcomponents under Different Levels of Variance Loss from Rounding

		Simulation parameters																							
		Autocorrelation						Within-strategy SD						Between-strategy correlation						Probability of Switching					
	Decimal place of rounding	None	5	4	3	2	1	None	5	4	3	2	1	None	5	4	3	2	1	None	5	4	3	2	1
Successive Difference	Full Index	-.80	-.80	-.80	-.80	-.80	-.80	.97	.97	.97	.97	.97	.97	.01	.01	.00	.00	.01	.01	.88	.88	.88	.88	.88	.88
	Replacement subcomponent	-.41	-.40	-.41	-.41	-.41	-.41	.80	.80	.80	.80	.80	.80	-.79	-.79	-.79	-.79	-.79	-.79	.88	.88	.88	.88	.88	.88
	Nestedness subcomponent	-.52	-.53	-.52	-.53	-.52	-.51	.88	.88	.88	.88	.88	.88	.74	.74	.74	.74	.74	.74	.03	.02	.02	.02	.02	.02
All-moment Comparisons	Full Index	-.43	-.43	-.43	-.44	-.43	-.42	.98	.98	.98	.98	.97	.97	.01	.01	.00	.01	.01	.01	.20	.20	.21	.21	.21	.21
	Replacement subcomponent	-.13	-.12	-.14	-.13	-.13	-.13	.83	.83	.83	.83	.83	.83	-.82	-.81	-.82	-.82	-.82	-.82	.19	.18	.18	.20	.20	.20
	Nestedness subcomponent	-.18	-.19	-.17	-.18	-.18	-.18	.90	.90	.90	.90	.90	.90	.78	.77	.78	.78	.78	.78	.01	.00	.00	.00	.00	.00

Note. We also presented the original results (from Table 2.2) under "none" for easy comparison. A smaller number of decimal place of rounding mimics a coarser scale-mapping process which has higher loss of true variance.

SUPPLEMENTAL MATERIAL 6: DESCRIPTIVE STATISTICS OF THE THREE REANALYZED DATASETS

Table S6

Means and Standard Deviations of the Variables (Rescaled to Range from 0 to 6) and Emotion Regulation Variability Indices (Range from 0 to 1) of the Three Reanalyzed Datasets (Blanke et al., 2020)

	Dataset 1 (N = 70; n_{max} = 5040)					**Dataset 2 (N = 95; n_{max} = 6239)**					**Dataset 3 (N = 70; n_{max} = 14098)**				
Variable/ER variability index	n	M	wSD	bSD	ICC	n	M	wSD	bSD	ICC	n	M	wSD	bSD	ICC
Mean NA	3824	1.40	0.84	0.90	0.50	5716	0.89	0.60	0.65	0.48	12293	0.72	0.54	0.50	0.40
Mean ER strategy rating	3812	1.87	0.71	0.70	0.47	5717	1.39	0.60	0.64	0.50	12293	1.27	0.58	0.68	0.55
Within-strategy SD	70	0.52	-	0.13	-	95	0.47	-	0.12	-	200	0.47	-	0.13	-
Between-strategy SD	3629	0.55	0.17	0.16	0.45	5573	0.49	0.18	0.17	0.44	11604	0.49	0.19	0.19	0.49
Between-strategy SD successive difference	3167	0.16	0.13	0.09	0.06	4989	0.17	0.14	0.05	0.08	10083	0.17	0.15	0.05	0.08
Bray-Curtis dissimilarity	3317	0.33	0.20	0.15	0.30	5114	0.39	0.17	0.16	0.42	10709	0.40	0.19	0.18	0.43
Replacement	3165	0.15	0.17	0.08	0.12	4983	0.20	0.18	0.10	0.20	10083	0.19	0.19	0.11	0.22
Nestedness	3165	0.15	0.14	0.09	0.06	4983	0.17	0.16	0.05	0.08	10083	0.18	0.17	0.06	0.09

Note. NA = negative affect; ER = emotion regulation; n_{max} = maximum number of moment-level observations in a dataset; *n* = number of observations; *M* = mean ;w*SD* = Within-person *SD*, or how much the variable varies within each participant; b*SD* = Between-person *SD,* or how much the variable varied between participants; ICC = intraclass correlation coefficient, or the percentage of variance of the variable that is due to differences between participants. Within-strategy *SD* has no w*SD* because it is calculated across all observations within a participant, thus have no variability within a participant. Due to this reason, no ICC is calculated for within-strategy *SD*.

SUPPLEMENTAL MATERIAL 7: MULTILEVEL MODELING RESULTS WITH UNSTANDARDIZED STANDARD DEVIATION

In Table S7, we present the model results based on unstandardized SD instead of relative SD, which is standardized by their maximum possible values given a mean level of ER (Mestdagh et al., 2018). We include the results from Table 2.4 from the main text for ease of comparison. SD-based indices remained less consistent than Bray-Curtis dissimilarity in predicting NA; they sometimes produced results that were difficult to interpret (e.g., positively predicted subsequent NA) which was likely due to the nonlinear mean-variance relationship that Mestdagh et al. (2018) cautioned against.

Table S7

Multilevel Results on Moment-Level and Person-Level Components of Emotion Regulation (ER) Variability Indices in Predicting Negative Affect in Three Datasets

	Fixed effect (Standard error)					
	Moment-level results			Person-level results		
	Dataset			Dataset		
ER variability index	1	2	3	1	2	3
Within-Strategy *SD*	(no moment-level results)			0.44 (0.33)	0.67*** (0.19)	0.55*** (0.09)
Between-Strategy *SD*	0.08 (0.05)	0.17*** (0.03)	0.13*** (0.02)	-0.65* (0.25)	0.65*** (0.13)	0.32*** (0.06)
Between-Strategy *SD* successive difference	0.01 (0.04)	0.03 (0.02)	0.06*** (0.02)	-1.08 (0.80)	-0.30 (0.42)	0.12 (0.21)
Within-Strategy *RSD*	(no moment-level results)			-2.35** (0.79)	-0.59 (0.58)	-0.70* (0.27)
Between-Strategy *RSD*	-0.33* (0.13)	0.11 (0.08)	0.05 (0.06)	-3.44*** (0.54)	-0.25 (0.39)	-0.53** (0.17)
Between-Strategy *RSD* successive difference	-0.01 (0.12)	-0.08 (0.07)	0.15** (0.05)	0.28 (1.59)	-3.94** (1.32)	-1.49* (0.72)
Bray-Curtis dissimilarity	-0.44*** (0.12)	-0.18** (0.06)	-0.12** (0.04)	-1.58* (0.65)	-1.92*** (0.29)	-1.58*** (0.17)
Replacement	-0.41** (0.14)	-0.23** (0.08)	-0.13** (0.04)	-2.75* (1.23)	-1.77** (0.56)	-1.21*** (0.28)
Nestedness	-0.38* (0.16)	-0.08 (0.08)	-0.03 (0.04)	-1.71 (1.46)	-2.94** (1.09)	-3.11*** (0.51)

Note. Moment-level results are based on the within-person component, person-level results are based on the between-person component. Fixed effect and random effect of intercept and time factor, random effect of the variability indices, autoregressive error-structure, and covariances between intercept and slopes were estimated but are not displayed. RSD: relative *SD* (Mestdagh et al., 2018).

* $p < .05$. ** $p < .01$. *** $p < .001$.

Appendix B

Supplemental Materials for Chapter 3 (Emotion Differentiation in Adolescents: Short-term Trade-offs with Regulation Variability and Emotion Intensity)

SUPPLEMENTAL MATERIALS 1: PRE-REGISTRATION, *A PRIORI* POWER ANALYSIS, AND DEVIATIONS

Pre-registration: the Original and Updated Version

On 04 May 2022, we submitted our original version of pre-registration [https://osf.io/9vx7t?revisionId=62723c863252440156414dd8&view_only=bbeadda0702c4a6696d906bbf8faaa83]. While we initially expected to have sufficient power to test our hypotheses usingthe G(F)ood together dataset from Radboud University, we are now using Bray-Curtis dissimilarity, a newly proposed emotion regulation variability (Lo et al., 2024), for testing our hypotheses. Therefore, we updated the power analysis. The new power analysis revealed that we are underpowered at 30% to test our hypotheses with multilevel modeling with only the G(F)ood together dataset. To ensure sufficient power, we decided to include more experience sampling method (ESM) datasets to test our hypotheses. We reached out to researchers who used ESM in Dutch-speaking regions with the same specified inclusion criteria in terms of frame of reference of ESM items and age group. We received favorable replies from researchers in accessing four ESM datasets, which provided us with a large enough sample size to reach 80% power. The pre-registered questions and hypotheses remained the same. We updated our pre-registration on 19 Oct 2023 prior to accessing the new datasets [https://osf.io/9vx7t?view_only=bbeadda0702c4a6696d906bbf8faaa83].

Updated Power Analysis

The pooled sample size across five datasets was 811. We used the PowerAnalysisIL Shiny app (Lafit et al., 2021) to calculate power for Hypothesis 1 (greater emotion differentiation at a given moment will result in heightened variability in emotion regulation at the subsequent moment) and Hypothesis 2 (variability in emotion regulation at one moment will not be associated with emotion differentiation at the following moment). We obtained parameters needed analyzing an unrelated ESM dataset collected by another researcher in Radboud University not involved in this specific project (Mosannenzadeh, 2021).

Hypothesis 1

Power analysis results for Hypothesis 1 are shown in Table S1.1. We concluded that power is likely to be over 80% when the final sample size approaches 800.

Table S1.1

Hypothesis 1 Power Analysis Results

Power Analysis Setup	
Parameter	Value
Outcome	Emotion regulation variability
Predictor	Emotion differentiation
Number of observations per participant	13
Fixed Intercept	3.208
Fixed Slope	-0.016
SD of error residual	0.636
Autocorrelation of level-1 errors	0.21
SD random intercept	0.738
SD random slope	0.027
Correlation (random intercept and random slope)	-0.174
Mean of predictor	3.221
SD of predictor	1.175
Estimate AR(1) correlated errors	Yes
Type I error	0.05
Monte Carlo Replicates	1000
Method	Maximizing the log-likelihood
Power Analysis Result	
Number of Participants	Simulated Power
100	0.186
300	0.46
500	0.681
700	0.796

Hypothesis 2

Power analysis results for Hypothesis 2 are shown in Table S1.2. For Hypothesis 2, there was already enough power by only just using the G(F)ood together dataset (N after exclusion criteria applied = 83).

Table S1.2

Hypothesis 2 Power Analysis Results

Power Analysis Setup	
Parameter	Value
Outcome	Emotion differentiation
Predictor	Emotion regulation variability
Number of observations per participant	13
Fixed Intercept	-1.75
Fixed Slope	-0.187
SD of error residual	2.583
Autocorrelation of level-1 errors	0.118
SD random intercept	0.514
SD random slope	0.417
Correlation (random intercept and random slope)	0.124
Mean of predictor	-2.883
SD of predictor	6.079
Estimate AR(1) correlated errors	Yes
Type I error	0.05
Monte Carlo Replicates	1000
Method	Maximizing the log-likelihood
Power Analysis Result	
Number of Participants	Simulated Power
80	0.938
90	0.966
100	0.984

Deviations from pre-registration

Our study had four minor deviations from its original pre-registration.

First, in section 19 and 28 (indices), we initially planned to use intraclass correlation coefficient (ICC) for between-person emotion differentiation to test the between-person Hypothesis 3 (stated as Hypothesis 1 in the original pre-registration). In our actual analyses, we did not use ICC, but the between-person component of the momentary emotion differentiation index (Erbas et al., 2021). We considered this deviation a better approach because the within-person and between-person hypotheses could be tested together. Momentary emotion differentiation index, derived from ICC, was shown to be statistically perfectly related to ICC (Erbas et al., 2021). This supports us using the momentary emotion differentiation index in substitution of ICC in testing Hypothesis 3.

Second, in section 22 (analysis plan), we initially planned to test the between-person Hypothesis 3 (originally Hypothesis 1 in the pre-registration) with hierarchical regressions. In our actual analysis, we instead tested this hypothesis by examining the fixed effect estimates of the time-invariant between-person components in multilevel models. Although a minor procedural deviation, this approach is statistically highly similar as the pre-registered approach. Just like the first deviation, we chose this because this approach allows us to test the within-person and between-person hypotheses could be tested together.

Third, in section 27 (data exclusion), we specified the exclusion of data with zero variance across all observations. However, we did not clarify if this zero variance criterion was to be applied at the item level (e.g., for a specific emotion like sadness) or at the factor level (e.g., for a group of related emotions such as sad, angry, depressed, and anxious, useful in calculating negative emotion intensity and differentiation). In our actual analysis, we opted for the factor-level application. This decision was based on the understanding that some items might not be relevant to participants (see Discussion), leading to zero ratings, but this would not necessarily indicate poor data quality if there was variance in other items within the same factor. Additionally, our dynamic indices evaluate multiple items, not just single ones. Applying the exclusion criterion at the factor level aligns more closely with our research objectives and ensures a more accurate assessment of data quality than excluding data based on single-item zero variance.

Fourth, in Section 28, we initially planned an exploratory analysis on the differentiation of positive emotions. Beyond this planned analysis, we conducted additional exploratory analyses: (a) within-person mediation on the temporal sequence from emotion differentiation to emotion regulation variability to emotion intensity, (b) an alternative specification of Bray-Curtis dissimilarity using the successive difference temporal comparison approach (Supplemental Materials 6), (c) the moderating effects of within-dataset age differences on our main hypotheses, and (d) the moderating effects of zero negative emotion (regulation) intensity on our main hypotheses.

SUPPLEMENTAL MATERIALS 2: PARTICIPANTS, PROCEDURES AND ESM MEASURES PER DATASET

Note that though descriptions of ESM measures are in English here, questionnaires were presented in Dutch to participants across the five studies.

We assessed the validity of ESM measures in four steps that were recognized as good practices given the current state of development in ESM measures validation (Vogelsmeier et al., 2023). First, we documented the reliability of measures in our samples (ESM Measures subsection in each dataset in Supplemental Materials 2). Second, we cited how these measures have been validated or used in earlier studies (Supplemental Materials 2). Third, we inspected the distributions of measures in our samples and compared them with those reported in earlier studies (Supplemental Materials 3). Fourth, we compared relations between measures in our samples against those reported in earlier studies (Supplemental Materials 3).

Most studies that we cited for the purpose of assessing ESM measures validity had samples with mean ages that fell between early to late adolescence (Sawyer et al., 2018): (In ascending order of age) (Schneiders et al., 2006; Achterhof et al., 2022; Bülow et al., 2022; Rauschenberg et al., 2017; Hasmi et al., 2017; Bennik, 2015; Barrantes-Vidal et al., 2013; Fried et al., 2022; Medland et al., 2020; J. M. Bakker et al., 2019; Brans et al., 2013). We also included studies with a wider age range but still covered adolescent participants (Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Delespaul & DeVries, 1987; Jacobs et al., 2007; Kiekens et al., 2023) and a few that covered only adults (Hartley et al., 2014; Myin-Germeys et al., 2000; Spence et al., 2014; van Eck et al., 1998). In the subsequent pages, where we detail each dataset we analyzed, the mean age and standard deviation of each sample are specified under the "Participants" headings.

Dataset 1: G(F)ood together, Radboud University (Verhagen et al., 2022)

Participants

This study was part of a larger project (G(F)ood together, in Dutch: G(V)oed voor elkaar; see van den Broek et al. (2020) for other details) that studied adolescents' eating behaviours and health with six longitudinal waves of data collection across 2017 to 2021 and one ESM study (in 2021) among Dutch adolescents and their parents. The study procedures were approved by the Ethics Committee Social Sciences of Radboud University, Nijmegen, the Netherlands (ECSW20170805-516). The ESM study was administered between the fifth and sixth wave in June and July 2021. An active parental consent procedure was used for the participation of the ESM study.

The goal for the ESM study was to recruit a subsample of 100 participants. 257 families whose parents or adolescents remained active at wave 5 of the G(F)ood together study were invited to participate in the ESM study, resulting in the inclusion of 89 adolescent participants (age M = 16.42, SD = 0.61) and one of their parents. After excluding observations in which each ESM item was completed in less than 500ms (potential careless responding) and excluding participants who showed zero variance across all ESM items, the final sample size consisted of 83 participants (age M = 16.43, SD = 0.68, female = 57.63%). Most of the participants were born in the Netherlands (97.59%).

Procedure

All participants completed the ESM using the SEMA-app (version 3, O'Brien et al., 2023) which they installed on their mobile phones a few days before starting the study. A semi-random sampling scheme was employed, with participants receiving 10 notifications per day at random moments within a fixed time interval spanning from 07.30 a.m. to 09.00 p.m. over seven consecutive days. Upon receiving a notification, participants had a 30-minute window to complete the ESM assessment. For the end-of-the-day assessment, a longer period of 149 minutes was allowed. In cases where participants did not open the momentary assessments, the app sent two reminders at 15 minutes and 25 minutes after the initial notification (75 minutes and 145 minutes for the end-of-the-day assessment). Participants responded to 3674 out of 6020 (61%) ESM notifications sent. The median number of assessments completed per participant was 47 out of 70 (67%; M = 41.83, SD = 17.06). All participants entered into a raffle for two €250 vouchers. Participants were paid at least €5 and up to €25 if they and their parents both had high compliance in the study.

ESM Measures

Emotions

At each momentary assessment, participants rated four positive emotions (content, relaxed, joyful, and energetic) and five negative emotions (irritated, worried, depressed, insecure, and lonely) presented in a randomized order on a 10-point slider scale (0 = not at all, 10 = a lot). The stem for these items was "Right now I feel [emotion]." These items have been used in other ESM studies (Achterhof et al., 2022; Bakker et al., 2019; Barge-Schaapveld et al., 1999; Barrantes-Vidal et al., 2013; Bastiaansen et al., 2018; Bennik, 2015; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006; van Eck et al., 1998). With 10 daily assessments over 7 days, the maximum possible number of measurements for negative and positive emotions was 70. Reliability was satisfactory for positive emotions (.70) and negative emotions (.66).

Emotion regulation strategies

At each even beep throughout the day (i.e., assessed five times daily), following the rating of negative emotions, participants responded to one additional question on a slider scale regarding the intensity of the most unpleasant event since the previous beep ("Think about the most unpleasant thing that you have experienced, since the last beep. How unpleasant was it?" 0= not at all unpleasant, 10 = very much unpleasant). If the unpleasantness was 5 or higher, participants had the opportunity to rate their use of emotion regulation strategies related to the event. This branching was introduced with a rationale of collecting reports with more intensive use of emotion regulation strategies. At the final beep of each day, regardless of event intensity, questions about emotion regulation strategies were asked. Adapted from Brans et al. (2013), for each of the five emotion regulation strategies listed below, participants rated their use on a 11-point scale (0 = not applicable at all, 10 = very applicable): acceptance ("I have accepted my feelings about it"), reappraisal ("to feel better, I have changed the way I think about it"), expression suppression ("I have avoided expressing my feelings about it"), rumination ("I couldn't stop thinking my feelings about it"), and sharing ("I talked about it to someone"). These strategies have been assessed in previous ESM studies (Hartley et al., 2014; Kiekens et al., 2023, 2023). With 5 even-beep assessments over 7 days, the maximum possible number of measurements for emotion regulation strategies was 35. Adolescents had a total of 719 beeps which they had the opportunity to report emotion regulation strategy use from 575 end-of-day beeps and 144 non-end-of-day even beeps which they rated having experienced a negative event with unpleasantness at 5 or above. Adolescents reported their use of emotion regulation strategies in 586 out of the 719 possible beeps (81.50%). Reliability was satisfactory for emotion regulation strategies (.59).

Dataset 2: Emotions in daily life 2011, KU Leuven (Koval, Pe, et al., 2013)

Participants

Participants were recruited from a pool of 439 undergraduates at the University of Leuven, Belgium, in a study which the ethics committee of the University of Leuven approved of. All undergraduates completed a Dutch translation of the Center for Epidemiologic Studies Depression Scale (CES-D, Radloff, 1977) and were further selected to maximize variation in depression scores. The target sample of 100 participants were contacted in 2011. Three participants were excluded because the devices they used had malfunction. There was no further exclusion based on careless responding (<500 ms) or zero variance instances. The final sample consisted of 97 participants. Mean age of the sample was 19.05 years (*SD* = 1.27), and 63% were women. Majority of the sample had Belgian nationality (97%).

Procedure

Participants took part in an introductory session in the laboratory, in which they gave informed consent to participate, filled out questionnaires unrelated to the current study, and received standardized devices (Tungsten E2 PalmOne, Mankato, MN), which were programmed to assess ESM items. The ESM study started the following day and lasted 7 days, during which 10 beeps occurred semi-randomly each day in a 12-hr time frame. Participants were informed that completing one measurement would take an average of 1 minute. Participants had to start the questionnaire within 2 minutes after the notification. Participants had 90 seconds to answer each question once they opened the questionnaire before it timed out. There were no reminders for participants in case they did not open the momentary assessments Participants answered 91.5% of the beeps (*SD* = 6.2%, range: 67–100% of all beeps). The participants were reimbursed with 70 Euros for the entire study.

ESM measures

Emotions

At each momentary assessment, participants rated two positive emotions (relaxed, happy) and four negative emotions (angry, sad, anxious, and depressed) presented on a 100-point slider scale (1 = not at all, 100 = very much). The stem for these items was "How [emotion] do you feel at the moment?" These items have been used in other ESM studies (Achterhof et al., 2022; Bakker et al., 2019; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Brans et al., 2013; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006). With 10 daily assessments over 7 days, the maximum possible number of measurements for negative and positive emotions was 70. Reliability was satisfactory for positive emotions (.71) and negative emotions (.76).

Emotion regulation strategies

At each momentary assessment, participants rated the extent they used six emotion regulation strategies presented on a 100-point slider scale (1 = not at all, 100 = very much so). The stem for these items was "Since the last beep, did you…" and ended with "ruminate about your feelings" (rumination), "calmly reflect on your feelings?" (reflection), "see the event that caused your feelings from a different perspective?" (reappraisal), "try to distract yourself from your feelings?" (distraction), "suppress the expression of your feelings?" (expressive suppression), and "talk with others about your feelings" (social sharing). These strategies have been assessed in previous ESM studies (Brans et al., 2013; Hartley et al., 2014; Kiekens et al., 2023, 2023; Medland et al., 2020). With 10 daily assessments over 7 days, the maximum possible number of measurements for emotion regulation strategies was 70. Reliability was satisfactory for emotion regulation strategies (.53).

Dataset 3: 3-wave longitudinal study, KU Leuven (Erbas et al., 2018)

Participants

Participants were undergraduates from the University of Leuven, Belgium. This three-wave study was approved by the ethics committee of the University of Leuven. Here, we only used the data from the first wave collected in 2012. 686 first-year undergraduates completed the Center for Epidemiologic Studies Depression Scale (CES-D, Radloff, 1977) as a prescreening questionnaire. 180 participants, formed by equal number of participants from four quartiles of the CES-D distribution, were selected following a stratified sampling approach. An additional 22 participants took part without completing the CES-D, resulting in a total of 202 participants. There were no participants excluded based on reaction time because reaction time was not available for ESM assessments in this dataset. No participants had zero variance across all ESM items, so the final sample was 202 participants. Mean age of the sample was 18.32 years (SD = 0.96), and 55% were women. Majority of the sample had Belgian nationality (93%).

Procedure

The participants took part in an introductory session in the laboratory and filled out questionnaires unrelated to the current study. Then, they received standardized devices (Motorola Defy Plus) with custom-built ESM software installed and were trained to use the phone to complete the ESM questionnaires. Participants practiced filling the ESM questionnaire and could clarify with an experimenter before leaving the lab. The ESM study lasted for 7 consecutive days, during which 10 beeps occurred semi-randomly each day in a 12-hr time frame. Participants were informed that completing one measurement would take an average of 1-2 minutes. Participants had 90 seconds to answer each question once they opened the questionnaire before it timed out. There were no reminders for participants in case they did not open the momentary assessments. Participants answered 87.27% of the beeps (SD = 9.05%, range: 67–100% of all beeps). The participants were reimbursed with 60 Euros for this wave of study. They were eligible for an extra 60 EUR reimbursement for completing all three waves of study.

ESM measures

Emotions

At each momentary assessment, participants rated three positive emotions (happy, relaxed, cheerful) and six negative emotions (lonely, angry, anxious, sad, depressed, and stressed) presented on a slider scale from 0 (not at all) to 100 (very much). The stem for these items was "How [emotion] do you feel at the moment?" These items have been used in other ESM studies (Achterhof et al., 2022; Bakker et al., 2019; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Brans et al., 2013; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006). With 10 daily assessments over 7 days, the maximum possible number of measurements for negative and positive emotions was 70. Reliability was satisfactory for positive emotions (.74) and negative emotions (.73).

Emotion regulation strategies

At each momentary assessment, participants rated the extent they used six emotion regulation strategies presented on a slider scale from 0 (not at all) to 100 (almost all the time). The stem for these items was "Since the last beep, have you…" and ended with "viewed the cause of your feelings from a different perspective?" (cognitive reappraisal), "suppressed the expression of your feelings" (expressive suppression), "distracted your attention away from your feelings" (distraction), "talked about your feelings with others" (social sharing), "brooded about something in the past" (rumination) and "brooded about something in the future" (worry). These strategies have been assessed in previous ESM studies (Achterhof et al., 2022; Bastiaansen et al., 2018; Brans et al., 2013; Hartley et al., 2014; Kiekens et al., 2023; Medland et al., 2020). With 10 daily assessments over 7 days, the maximum possible number of measurements for emotion regulation strategies was 70. Reliability was satisfactory for emotion regulation strategies (.52).

Dataset 4: Emotion regulation in daily life, Tilburg University (Van Roekel & Trompetter, 2023)

Participants

Participants were undergraduates from Tilburg University, the Netherlands. This study was approved by the ethics committee of the Tilburg School of Social and Behavioral Sciences (protocol number: EC-2017.95). Data were collected in 2018. 242 first-year undergraduates who needed to earn course credits were recruited. For this study, only data from participants who were younger than 25 years old were used. Therefore, the initial sample consisted of 179 participants (age M = 20.84 , *SD* = 1.67). After excluding participants who had zero variance across all ESM items, there was a final sample of 178 participants. There were no participants excluded based on reaction time because reaction time was not available for ESM assessments in this dataset. Mean age of the sample was 20.85 years (*SD* = 1.67), and 78% were women. Majority of the sample was born in the Netherlands (93%).

Procedure

Participants were recruited through the University course credit system, where they were able to read information about the research and could register via the same system. To participate, students had to click a link in an information letter sent to them by email. There, they signed informed consent and completed a questionnaire with baseline data that were not relevant for this study. The email also instructed participants to download the app "Ethica" (www.ethicadata.com) on their smartphone for the ESM assessments.

The ESM period started within a few days after completing the baseline questionnaires. The ESM study lasted for 14 consecutive days, during which the Ethica app gave 5 beeps quasi-randomly each day in a 12-hr time frame. The participants had to complete the questionnaire within 30 minutes after the notification. Participants were informed that completing one measurement would take an average of 3 minutes. In cases where participants did not open the momentary assessments, the app sent a reminder after the initial notification, but the details of the notification setting were lost due to interface change of Ethica. The median number of completed assessments per participant was 52 out of 70 (73.97%, M = 66.36% , SD = 23.50%, range: 5.35–98.63% of all beeps). When the 14 days were over, the study was completed and the participants were rewarded with 4 test credits for participants recruited via the Tilburg course credit system or a chance of winning 30-Euro shopping vouchers for participants recruited via other channels.

ESM measures

Emotions

At each momentary assessment, participants rated seven positive emotions (enthusiastic, content, energetic, calm, powerful, cheerful, and grateful) and six negative emotions (irritated, bored, nervous, sad, angry, and depressed) presented on a slider scale from 0 (not at all) to 100 (very much). The stem for these items was "I now feel (right before the beep went off) [emotion]." These items have been used in other ESM studies (Achterhof et al., 2022; Bakker et al., 2019; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006; Spence et al., 2014). With 10 daily assessments over 7 days, the maximum possible number of measurements for negative and positive emotions was 70. Reliability was satisfactory for positive emotions (.80) and negative emotions (.69).

Emotion regulation strategies

At each momentary assessment, participants rated the extent they used seven emotion regulation strategies presented on a slider scale from 0 (not at all) to 100 (very much). Based on theoretical frameworks of Aldao et al. (2010) and Parkinson & Totterdell (1999), the stem for these items was "Indicate to what extent you have used each of the following strategies since the last beep, regardless of whether they helped. To change my negative emotions, I have…" and ended with "addressed the situation that caused my emotions or have made plans for addressing it" (problem solving), "brooded my emotions with others" (co-brooding), "sought distraction" (distraction), "suppressed, ignored or avoided (the thoughts about) my emotions or the situation that caused them." (avoidance), "talked about my feelings with others for advice or support" (social sharing), "been thinking about my feelings and their causes and/or consequences" (rumination) and "experienced my emotions as they are without wanting them change: it is OK that they are there" (acceptance). Rumination, acceptance, social sharing, and distraction have been assessed in previous ESM studies (Achterhof et al., 2022; Kiekens et al., 2023). With 10 daily assessments over 7 days, the maximum possible number of measurements for emotion regulation strategies was 70. Reliability was satisfactory for emotion regulation strategies (.53).

Dataset 5: Outside-in, Ghent University (Braet et al., 2023)

Participants

244 students were recruited from local schools in Belgium (age M = 13.46, SD = 0.42; female = 48%). This 3-wave study was approved by the Medical Ethics Committee of Ghent University Hospital (protocol number: BC-09559). For our analysis, we only utilized data from the third wave, which was collected in 2022. This choice ensures that participants from this study have a closer age range to participants in other studies. After excluding observations in which each ESM item was completed in less than 500ms and excluding participants who showed zero variance across all ESM items, the final sample consisted of 212 participants. Mean age of the sample was 13.46 years (SD = 0.42), and 44% were female. Majority of the sample were born to Belgian parents (90%).

Procedure

Participants were recruited through nine different schools (Flanders region). Parental consent and written assent from adolescents were obtained. All participants installed the m-Path app on their smartphones (www.m-path.io, Mestdagh et al., 2023). The ESM period started within a few days after completing different baseline questionnaires. The ESM study lasted for 14 consecutive days during school weeks, during which the m-path app gave 5 beeps at fixed intervals each day in a 12-hr time frame. One measurement took an average of 2 minutes. The participants had 50 to 120 minutes after the notification to complete the questionnaire (first to third beep of the day: 50 minutes, fourth beep of the day: 90 minutes, and last beep of the day: 120 minutes). In cases where participants did not open the momentary assessments, the app sent reminders every 10 minutes after the initial notification. Compliance rate was also monitored during the study for each participant, after two days of low compliance participants received a message via m-path. Out of all participants, one discontinued the study after seven days, thus only receiving 35 beeps. Two participants encountered technical issues that prevented them from receiving some beeps on weekends, resulting in only 52 and 56 beeps received. Another 27 participants experienced occasional technical issues, receiving 65 to 69 beeps over the course of 14 days. The median number of assessments completed per participant was 49 out of 70 (70%, M = 64.51% , SD = 24.97%, range: 1.4%–100% of all possible beeps). When the 14 days were over, the study was completed and the participants were rewarded with a gift voucher worth €20 when they completed at least 70% of surveys, while a voucher of €10 was given to those who completed between 50% and 70% of surveys.

ESM measures

Emotions

At each momentary assessment, participants rated three positive emotions (happy, energetic, and relaxed) and six negative emotions (sad, angry, anxious, uncertain, annoyed, and stressed) presented on a 7-point scale from 1 (totally not) to 7 (totally). The stem for these items was "I now feel: [emotion]." These items have been used in other ESM studies (Achterhof et al., 2022; Bakker et al., 2019; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Brans et al., 2013; Bülow et al., 2022; Delespaul & DeVries, 1987; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006). With 5 daily assessments over 14 days, the maximum possible number of measurements for negative and positive emotions was 70. Reliability was satisfactory for positive emotions (.60) and negative emotions (.69).

Emotion regulation strategies

First, participants reported the intensity of their experienced negative emotions since the last survey (or after waking up). In case no negative emotion was experienced, participants were instructed to respond with a score of 1. Then, Participants rated the extent they used eight emotion regulation strategies presented on a 7-point scale from 1 (totally not) to 7 (totally). The stem for these items was "When I felt those negative emotions…." With reference to Medland et al. (2020), five items ended with "I tried to see the situation in other ways" (cognitive reappraisal), "I tried to hide my emotions" (expressive suppression), "I did things to distract myself" (distraction), "I could not stop thinking about them" (rumination), and "I tried to express my emotions" (expression). Next, one item was added to assess social sharing, "I talked with someone else about the situation" (social sharing). These strategies have been assessed in previous ESM studies (Achterhof et al., 2022; Bastiaansen et al., 2018; Brans et al., 2013; Hartley et al., 2014; Kiekens et al., 2023). Finally, based on Berking & Znoj (2011), two more self-compassion items were included: "I have supported myself" (self-compassion) and "I tried to cheer up myself" (self-compassion). With 5 daily assessments over 14 days, the maximum possible number of measurements for emotion regulation strategies was 70. Reliability was satisfactory for emotion regulation strategies (.72).

SUPPLEMENTAL MATERIALS 3: DISTRIBUTIONS, DESCRIPTIVE STATISTICS AND CORRELATIONS OF MEASURES

Distributions of Momentary Indices

We visually inspected the distributions of within-person means, standard deviations, and skewness values of all momentary indices calculated from ESM measures (Figure S3). All indices have comparable means and standard deviations with earlier ESM studies that reported emotion intensity (Bennik, 2015; Bülow et al., 2022; Jacobs et al., 2007; Rauschenberg et al., 2017; Schneiders et al., 2006), emotion differentiation (Emery et al., 2022; Erbas et al., 2021; Knapp et al., 2024; Lischetzke et al., 2021), and emotion regulation variability (Lo et al., 2024).

Referencing to von Klipstein et al., (2023)'s procedures in assessing potential floor or ceiling effects, we noticed that negative emotion intensity, emotion regulation intensity, and the strategy switching subcomponent of emotion regulation variability have some mean values close to the lower bound of the scale, indicating potential floor effects. We further checked the proportion of zero values in these indices across persons and across measurements (Table S3). Across all ESM measurements, 18.62% of ratings for negative emotion intensity and 15.02% for emotion regulation intensity were zero. However, these percentages are significantly lower than the 51.7% zero-rating proportion reported in von Klipstein et al. (2023), with which they demonstrated a floor effect in negative emotion intensity in their sample. The comparatively lower proportions in our samples suggest a lesser extent of floor effects, if present at all. Despite the potential floor effects, the distribution of negative emotion differentiation is comparable to that of positive emotion differentiation, originating from normally distributed positive emotion intensities. Moreover, emotion regulation variability calculations inherently control for emotion regulation intensity, protecting against floor effects. This is evident from a very low proportion of zero values across adolescents and ESM measurements in emotion regulation variability. Interestingly, the strategy switching subcomponent of emotion regulation variability has the highest proportion of floored within-person mean and SD, and is among the indices with highest proportion of floored values at ESM measurement-level. So, for some adolescents, their emotion regulation variability is solely comprised of the endorsement change subcomponent. This means that these adolescents varied the *intensity* of the same strategies but seldom change varied their strategy *selection*. Our confirmatory hypotheses primarily focused on negative emotion differentiation and the full index of emotion regulation variability. Based on the observed distribution patterns, we deemed it appropriate to use these indices for testing the confirmatory hypotheses. That said, our exploratory analyses included negative emotion intensity as an outcome variable. To address this, in Supplemental Materials 8, we conducted sensitivity analyses to examine whether the presence of zero emotion (regulation) intensity moderated the effects tested in our study.

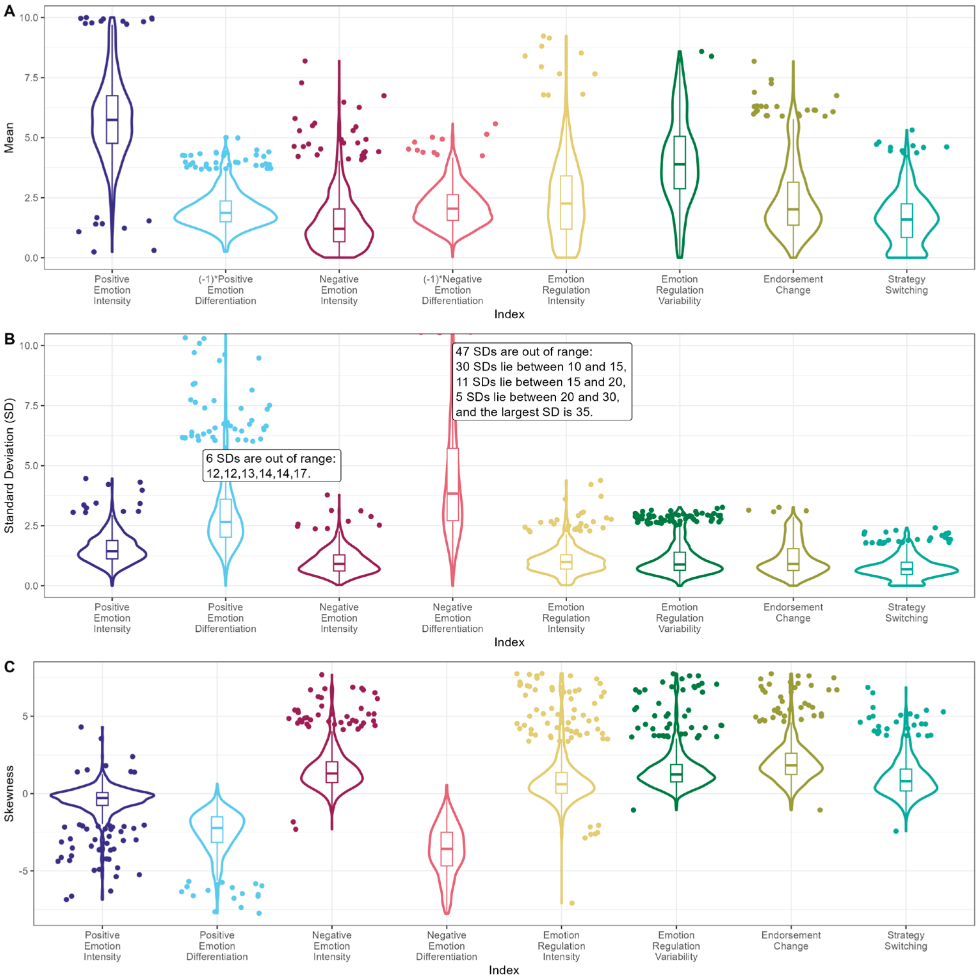
Table S3.1

Proportion of Zero Values on Momentary Indices Across Persons and Across ESM Measurements

Momentary index	Within-person Mean	Within-person SD	Across all ESM Measurements
Positive emotion intensity	0.00%	0.13%	0.95%
Positive emotion differentiation	0.00%	0.00%	0.03%
Negative emotion intensity	0.00%	0.00%	18.62%
Negative emotion differentiation	0.00%	0.13%	0.03%
Emotion regulation intensity	0.00%	0.00%	15.02%
Emotion regulation variability (full index)	0.52%	0.91%	0.01%
Endorsement change subcomponent	0.52%	0.91%	0.01%
Strategy switching subcomponent	4.52%	4.55%	15.89%

Figure S3

Combined violin plots and box plots of the within-person means (M; Panel A), within-person standard deviations (SD; Panel B), and within-person skewness (Panel C) of momentary indices derived from ESM measurements



Note. The outer shapes represent the mirrored density function, encompassing box plots. The thick central line in the box plot marks the median, while the bottom and top edges of the rectangle show the 25th and 75th percentiles, respectively. Vertical lines stretch beyond these percentiles to a maximum of 1.5 times the inter-quartile range, and dots represent values outside this range of the vertical lines. Note that in Panel A, we inverted the negative values of means of positive and negative emotion differentiation to positive values to ease comparison.

Descriptive Statistics and Correlations of Measures

We further inspected the descriptive statistics, within-person correlations and between-person correlations of momentary indices (Table S3.1 to S3.2.5) and ESM measures (Table S3.3.1 to S3.3.5). First, between positive and negative emotion intensity, there were negative within-person and between-person correlations, matching previous ESM studies that reported such negative within-person correlations (Springstein et al., 2023) and between-person correlations (Schneiders et al., 2006; van Eck et al., 1998). Second, between any pairs of positive/negative emotion differentiation and positive/negative emotion intensity, their within-person and between-person correlations matched in directions and were of comparable strengths with previous ESM studies that reported such correlations (Knapp et al., 2024; Lischetzke et al., 2021; Springstein et al., 2023). Third, between negative emotion intensity and emotion regulation variability, although within-person correlations were not consistent in directions across datasets, negative between-person correlations between negative emotion intensity and emotion regulation variability (and its endorsement subcomponent) matched previous reports (Lo et al., 2024). Overall, correlations between momentary indices in our pooled dataset were generally in line with previous ESM studies, supporting us to further analyze these indices.

Table S3.2

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in the Pooled Dataset (N=778)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	39286	5.78	1.65	1.53	2.16	8.54		.27 [.20, .33]	-.44 [-.50,-.39]	.14 [.07, .21]	-.03 [-.10, .05]	-.12 [-.19,-.05]	.03 [-.04, .10]	-.24 [-.31,-.18]
2. Positive emotion differentiation	39230	-1.98	0.76	3.06	-15.25	-0.03	.23 [.22, .24]		-.10 [-.16,-.02]	.24 [.17, .30]	-.02 [-.10, .05]	.00 [-.07, .07]	.03 [-.04, .10]	-.05 [-.12, .02]
3. Negative emotion intensity	39179	1.46	1.16	0.98	0.3	4.57	-.45 [-.46,-.44]	-.19 [-.20,-.18]		-.26 [-.32,-.19]	.41 [.35, .47]	-.10 [-.17,-.03]	-.20 [-.26,-.13]	.11 [.04, .18]
4. Negative emotion differentiation	39179	-2.15	0.82	4.8	-28.26	-0.03	.22 [.21, .23]	.28 [.28, .29]	-.51 [-.52,-.50]		-.07 [-.14, .00]	-.02 [-.09, .05]	-.04 [-.11, .03]	.03 [-.04, .10]
5. Emotion regulation intensity	36383	2.28	1.62	1.06	0.78	5.08	-.10 [-.11,-.09]	-.06 [-.07,-.05]	.28 [.27, .29]	-.16 [-.17,-.15]		-.24 [-.31,-.17]	-.40 [-.45,-.34]	.14 [.07, .21]
6. Emotion regulation variability	36218	4.03	1.78	1.13	3.04	7.29	-.03 [-.04,-.02]	-.11 [-.12,-.10]	.06 [.05, .07]	-.15 [-.16,-.14]	-.04 [-.05,-.03]		.81 [.79, .83]	.57 [.52, .61]
7. Endorsement change	36218	2.35	1.47	1.13	1.5	6.12	-.01 [-.02, .00]	-.07 [-.08,-.06]	.04 [.03, .05]	-.13 [-.14,-.12]	-.04 [-.05,-.03]	.76 [.75, .76]		-.02 [-.09, .05]
8. Strategy switching	36218	1.68	1.05	0.75	0.38	3.65	-.03 [-.04,-.02]	-.06 [-.07,-.05]	.03 [.02, .04]	-.02 [-.03,-.01]	-.01 [-.02, .00]	.34 [.33, .35]	-.36 [-.36,-.35]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.3.1

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in Dataset 1: G(F)ood together (Radboud)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	3384	6.76	1.19	1.14	3.97	8.64		.39 [.19, .56]	-.64 [-.75,-.49]	.41 [.21, .57]	.00 [-.22, .22]	-.07 [-.28, .16]	.03 [-.19, .25]	-.18 [-.38, .04]
2. Positive emotion differentiation	3384	-1.92	0.61	2.78	-13.62	-0.02	.30 [.27, .33]		-.38 [-.55,-.18]	.53 [.35, .67]	-.04 [-.26, .18]	-.13 [-.34, .10]	-.04 [-.26, .18]	-.13 [-.34, .09]
3. Negative emotion intensity	3331	1.29	1.13	0.9	0.23	3.8	-.54 [-.56,-.51]	-.23 [-.27,-.20]		-.35 [-.52,-.14]	.09 [-.13, .30]	-.07 [-.28, .16]	-.16 [-.37, .06]	.20 [-.02, .40]
4. Negative emotion differentiation	3331	-1.81	0.68	3.41	-18.09	-0.03	.28 [.24, .31]	.34 [.31, .37]	-.50 [-.53,-.47]		.10 [-.12, .32]	-.17 [-.38, .05]	-.07 [-.28, .16]	-.17 [-.38, .05]
5. Emotion regulation intensity	583	3.48	1.48	1.58	1.67	5.78	-.16 [-.24,-.08]	-.14 [-.22,-.06]	.22 [.14, .30]	-.12 [-.21,-.04]		-.52 [-.67,-.34]	-.61 [-.73,-.45]	.28 [.06, .47]
6. Emotion regulation variability	583	4.28	1.87	1.21	3.38	6.55	.00 [-.09, .08]	-.04 [-.12, .04]	-.01 [-.09, .08]	-.03 [-.12, .05]	-.20 [-.28,-.13]		.85 [.78, .90]	.07 [-.15, .28]
7. Endorsement change	583	2.93	2.11	1.13	2.17	5.16	.04 [-.05, .12]	.02 [-.07, .10]	-.04 [-.12, .05]	-.01 [-.10, .07]	-.26 [-.34,-.19]	.83 [.80, .85]		-.46 [-.62,-.27]
8. Strategy switching	583	1.34	1.11	0.67	0.63	2.5	-.07 [-.15, .02]	-.09 [-.17,-.01]	.05 [-.03, .13]	-.03 [-.12, .05]	.10 [.02, .18]	.28 [.20, .35]	-.31 [-.39,-.24]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.3.2

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in Dataset 2: Emotions in daily life (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	5816	5.67	1.32	1.75	1.62	8.96		.16 [-.04, .35]	-.62 [-.73,-.48]	.21 [.01, .40]	-.23 [-.41,-.03]	.18 [-.02, .36]	.21 [.01, .39]	.07 [-.13, .27]
2. Positive emotion differentiation	5816	-1.49	0.2	2.05	-10.47	0	.21 [.19, .24]		-.04 [-.24, .16]	.27 [.07, .44]	-.10 [-.29, .10]	.00 [-.20, .20]	.04 [-.16, .24]	-.04 [-.24, .16]
3. Negative emotion intensity	5814	1.47	1.08	0.99	0.24	4.79	-.48 [-.50,-.46]	-.17 [-.20,-.15]		-.41 [-.57,-.23]	.61 [.47, .72]	-.50 [-.64,-.33]	-.48 [-.62,-.31]	-.32 [-.49,-.13]
4. Negative emotion differentiation	5814	-2.05	0.48	4.8	-30.11	0	.26 [.24, .29]	.33 [.31, .35]	-.54 [-.56,-.52]		-.30 [-.47,-.11]	.13 [-.08, .32]	.11 [-.09, .31]	.09 [-.11, .28]
5. Emotion regulation intensity	5815	2.32	1.06	1	0.63	5.2	-.14 [-.17,-.12]	-.07 [-.09,-.04]	.37 [.35, .40]	-.24 [-.26,-.21]		-.66 [-.76,-.53]	-.72 [-.80,-.61]	-.33 [-.49,-.14]
6. Emotion regulation variability	5815	4.48	1.48	0.85	3.44	7.13	.03 [.01, .06]	-.08 [-.10,-.05]	-.06 [-.09,-.04]	-.09 [-.11,-.06]	-.19 [-.21,-.16]		.83 [.75, .88]	.78 [.69, .85]
7. Endorsement change	5815	2.32	0.96	0.93	1.28	5.8	.01 [-.01, .04]	.00 [-.03, .02]	.00 [-.03, .02]	-.10 [-.13,-.08]	-.05 [-.08,-.03]	.54 [.52, .56]		.30 [.11, .47]
8. Strategy switching	5815	2.17	0.87	0.87	0.44	4.66	.02 [-.01, .04]	-.07 [-.10,-.05]	-.06 [-.09,-.04]	.03 [.00, .05]	-.13 [-.15,-.10]	.40 [.38, .42]	-.55 [-.57,-.53]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.3.3

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in Dataset 3: 3-wave longitudinal study (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	12346	5.69	1	1.63	1.85	8.94		.21 [.07, .34]	-.45 [-.55,-.33]	.25 [.11, .37]	-.28 [-.40,-.15]	.13 [.00, .27]	.21 [.07, .33]	-.05 [-.19, .09]
2. Positive emotion differentiation	12346	-1.88	0.36	2.63	-13.19	0	.15 [.13, .17]		-.22 [-.35,-.09]	.27 [.14, .39]	-.22 [-.35,-.08]	.10 [-.04, .23]	.16 [.02, .29]	-.05 [-.19, .09]
3. Negative emotion intensity	12346	1.48	0.88	0.94	0.26	4.65	-.53 [-.55,-.52]	-.22 [-.24,-.20]		-.40 [-.51,-.28]	.72 [.64, .78]	-.51 [-.61,-.40]	-.53 [-.62,-.42]	-.19 [-.32,-.05]
4. Negative emotion differentiation	12346	-2.3	0.81	5.07	-31.81	0	.24 [.22, .25]	.33 [.31, .34]	-.54 [-.55,-.53]		-.37 [-.48,-.25]	.20 [.07, .33]	.20 [.06, .32]	.10 [-.04, .24]
5. Emotion regulation intensity	12346	2.11	1.13	0.96	0.5	4.86	-.17 [-.19,-.15]	-.08 [-.10,-.06]	.34 [.32, .35]	-.20 [-.22,-.19]		-.61 [-.69,-.52]	-.70 [-.76,-.62]	-.13 [-.26, .01]
6. Emotion regulation variability	12346	4.57	1.6	0.95	3.51	7.44	.03 [.02, .05]	-.09 [-.11,-.07]	-.01 [-.03, .01]	-.09 [-.11,-.08]	-.18 [-.20,-.16]		.86 [.82, .89]	.63 [.54, .71]
7. Endorsement change	12346	2.6	1.25	1.06	1.51	6.39	.03 [.01, .04]	-.04 [-.06,-.02]	.00 [-.01, .02]	-.09 [-.10,-.07]	-.13 [-.15,-.12]	.57 [.56, .59]		.15 [.02, .29]
8. Strategy switching	12346	1.96	0.82	0.93	0.31	4.67	.00 [-.01, .02]	-.05 [-.07,-.03]	-.02 [-.03, .00]	.00 [-.02, .02]	-.03 [-.05,-.02]	.38 [.37, .40]	-.54 [-.55,-.53]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.3.4

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in Dataset 4: Emotion regulation in daily life (Tilburg)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	7904	4.58	1.17	1.28	1.95	7.09		-.06 [-.20, .09]	-.20 [-.34,-.05]	.00 [-.15, .15]	.19 [.04, .33]	-.13 [-.27, .02]	-.14 [-.28, .01]	-.02 [-.17, .12]
2. Positive emotion differentiation	7904	-2.95	0.79	3.94	-18.14	-0.06	.13 [.11, .15]		-.01 [-.16, .14]	.32 [.19, .45]	-.10 [-.25, .05]	-.16 [-.30,-.01]	-.13 [-.27, .02]	-.09 [-.23, .06]
3. Negative emotion intensity	7852	1.54	0.93	0.92	0.45	4.32	-.47 [-.49,-.46]	-.21 [-.23,-.18]		-.32 [-.44,-.18]	.63 [.53, .71]	-.29 [-.42,-.15]	-.31 [-.44,-.17]	-.07 [-.21, .08]
4. Negative emotion differentiation	7852	-2.15	0.8	4.31	-23.6	-0.02	.27 [.25, .29]	.33 [.31, .35]	-.57 [-.58,-.55]		-.31 [-.44,-.17]	.09 [-.06, .24]	.09 [-.06, .24]	.03 [-.12, .17]
5. Emotion regulation intensity	7802	2.32	1.08	0.9	0.92	4.71	.00 [-.03, .02]	-.05 [-.07,-.03]	.25 [.23, .27]	-.16 [-.18,-.14]		-.41 [-.53,-.28]	-.55 [-.65,-.44]	.07 [-.08, .21]
6. Emotion regulation variability	7637	3.88	1.43	0.86	2.89	6.22	-.08 [-.10,-.06]	-.15 [-.17,-.12]	.08 [.06, .11]	-.18 [-.20,-.15]	-.03 [-.05,-.01]		.81 [.75, .86]	.58 [.48, .67]
7. Endorsement change	7637	2.13	1.19	0.84	1.25	4.79	.00 [-.02, .03]	-.06 [-.08,-.03]	.00 [-.03, .02]	-.09 [-.11,-.07]	-.08 [-.10,-.06]	.62 [.60, .63]		.00 [-.15, .15]
8. Strategy switching	7637	1.75	0.87	0.76	0.56	3.88	-.10 [-.12,-.08]	-.11 [-.13,-.08]	.10 [.08, .12]	-.10 [-.12,-.08]	.05 [.03, .07]	.46 [.44, .48]	-.41 [-.43,-.40]	

*Note***. SDw:** Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.3.5

Descriptive Statistics, Within- and Between-person Correlations of Momentary Indices in Dataset 5: Outside-in (Ghent)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Positive emotion intensity	9836	6.58	2.11	1.7	2.19	9.12		-.09 [-.23, .04]	-.51 [-.60,-.40]	.09 [-.04, .22]	-.08 [-.21, .05]	-.27 [-.39,-.14]	-.13 [-.26, .00]	-.30 [-.42,-.17]
2. Positive emotion differentiation	9780	-1.63	0.55	3.3	-17.55	-0.05	.36 [.35, .38]		-.05 [-.18, .08]	.37 [.25, .48]	.05 [-.08, .18]	-.03 [-.16, .11]	-.12 [-.25, .02]	.13 [.00, .26]
3. Negative emotion intensity	9836	1.42	1.55	1.11	0.27	4.91	-.33 [-.35,-.31]	-.17 [-.19,-.15]		-.14 [-.27,-.01]	.37 [.25, .48]	.22 [.09, .34]	.01 [-.13, .14]	.39 [.27, .50]
4. Negative emotion differentiation	9836	-2.15	0.96	5.48	-31.81	-0.06	.17 [.15, .19]	.24 [.22, .26]	-.45 [-.46,-.43]		.02 [-.11, .15]	-.18 [-.31,-.05]	-.27 [-.39,-.14]	.07 [-.06, .20]
5. Emotion regulation intensity	9837	2.35	2.3	1.1	0.68	5.27	-.06 [-.08,-.04]	-.04 [-.06,-.02]	.21 [.19, .23]	-.10 [-.12,-.08]		.01 [-.13, .14]	-.27 [-.39,-.14]	.42 [.30, .52]
6. Emotion regulation variability	9837	3.19	2.05	1.62	2.42	8.36	-.09 [-.11,-.07]	-.11 [-.13,-.09]	.14 [.12, .15]	-.19 [-.21,-.17]	.08 [.06, .10]		.84 [.79, .87]	.57 [.47, .65]
7. Endorsement change	9837	2.2	1.69	1.53	1.55	7.45	-.06 [-.08,-.04]	-.10 [-.12,-.08]	.10 [.08, .12]	-.19 [-.20,-.17]	.06 [.04, .08]	.92 [.92, .92]		.03 [-.11, .16]
8. Strategy switching	9837	0.99	1.12	0.56	0.2	2.51	-.08 [-.10,-.06]	-.03 [-.05,-.01]	.10 [.08, .12]	-.04 [-.06,-.02]	.06 [.04, .08]	.31 [.29, .33]	-.09 [-.11,-.07]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.1.1

Descriptive Statistics, Within- and Between-person Correlations of Positive Emotions in Dataset 1: G(F)ood together (Radboud)

	n	M	SDw	SDb	Min	Max	1	2	3	4
1. Content	3489	7.12	1.27	1.39	3.17	9.18		.83 [.75,.89]	.90 [.85,.94]	.67 [.53,.77]
2. Relaxed	3498	6.64	1.34	1.79	2.11	9.17	.38 [.35,.41]		.77 [.66,.84]	.58 [.42,.71]
3. Joyful	3498	7.08	1.28	1.43	3.18	9.23	.50 [.48,.53]	.36 [.33,.39]		.72 [.59,.81]
4. Energetic	3487	6.19	1.41	1.75	2.02	8.89	.35 [.32,.38]	.22 [.18,.25]	.47 [.44,.49]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.1.2

Descriptive Statistics, Within- and Between-person Correlations of Negative Emotions in Dataset 1: G(F)ood together (Radboud)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5
1. Irritated	3483	1.41	1.23	1.58	0.07	6.36		.45 [.26,.61]	.54 [.36,.68]	.56 [.40,.70]	.42 [.22,.58]
2. Worried	3493	1.52	1.36	1.51	0.12	5.87	.24 [.21,.27]		.79 [.70,.86]	.67 [.53,.78]	.58 [.42,.71]
3. Depressed	3487	1.14	1.24	1.25	0.13	4.76	.30 [.27,.33]	.33 [.30,.36]		.69 [.56,.79]	.76 [.65,.84]
4. Insecure	3492	1.44	1.8	1.17	0.22	4.75	.23 [.19,.26]	.37 [.34,.40]	.40 [.37,.43]		.74 [.62,.82]
5. Lonely	3483	0.96	1.1	1.2	0.04	4.69	.17 [.13,.20]	.19 [.16,.22]	.36 [.33,.39]	.32 [.29,.35]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.1.3

Descriptive Statistics, Within- and Between-person Correlations of Emotion Regulation Strategies in Dataset 1: G(F)ood together (Radboud)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5
1. Acceptance	585	5.73	2.62	2.58	2.24	8.68		.51 [.32,.65]	.18 [-.04,.39]	-.05 [-.26,.17]	.10 [-.12,.31]
2. Reappraisal	585	3.69	2.44	2.55	1.12	7.39	.38 [.31,.44]		.39 [.19,.56]	.23 [.01,.43]	.30 [.09,.49]
3. Suppression	585	3.4	2.27	2.7	0.82	7.36	.17 [.09,.25]	.32 [.25,.39]		.59 [.42,.71]	.10 [-.12,.31]
4. Rumination	584	2.39	1.97	2.2	0.49	5.82	-.03 [-.11,.05]	.19 [.11,.27]	.37 [.30,.44]		.24 [.02,.44]
5. Social Sharing	583	2.23	2.28	2.48	0.35	6.16	.10 [.01,.18]	.15 [.07,.23]	.18 [.10,.26]	.34 [.26,.41]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.2.1

Descriptive Statistics, Within- and Between-person Correlations of Positive Emotions in Dataset 2: Emotions in daily life (Leuven)

	n	M	SDw	SDb	Min	Max	1	2
1. Relaxed	5818	5.78	1.28	2.1	0.99	9.46		.80 [.72,.86]
2. Happy	5818	5.57	1.5	1.89	1.27	9.17	.55 [.53,.57]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.2.2

Descriptive Statistics, Within- and Between-person Correlations of Negative Emotions in Dataset 2: Emotions in daily life (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4
1. Angry	5819	1.33	0.96	1.35	0.05	6.37		.65 [.51,.75]	.64 [.51,.75]	.68 [.55,.77]
2. Anxious	5818	1.24	1.07	1.13	0.06	5.38	.31 [.29,.34]		.78 [.68,.84]	.78 [.69,.85]
3. Depressed	5818	1.6	1.48	1.26	0.15	5.6	.39 [.37,.41]	.38 [.36,.40]		.94 [.91,.96]
4. Sad	5817	1.7	1.28	1.46	0.1	6.39	.39 [.37,.41]	.39 [.37,.41]	.64 [.63,.66]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.2.3

Descriptive Statistics, Within- and Between-person Correlations of Emotion Regulation Strategies in Dataset 2: Emotions in daily life (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6
1. Distraction	5817	2.89	1.66	1.99	0.28	7.92		.51 [.34,.64]	.42 [.24,.57]	.41 [.23,.56]	.30 [.11,.48]	.62 [.48,.73]
2. Reappraisal	5817	1.76	1.17	1.39	0.16	6.23	.10 [.08,.13]		.78 [.68,.85]	.33 [.14,.50]	.67 [.54,.77]	.42 [.24,.57]
3. Reflection	5817	2.27	1.25	1.79	0.19	7.48	.06 [.03,.08]	.30 [.27,.32]		.41 [.23,.56]	.64 [.51,.75]	.33 [.14,.50]
4. Rumination	5817	2.65	1.71	1.91	0.17	7.67	.03 [.00,.05]	.17 [.15,.20]	.31 [.29,.33]		.37 [.18,.53]	.59 [.45,.71]
5. Social Sharing	5817	2.07	1.23	1.95	0.08	7.69	.05 [.03,.08]	.24 [.22,.26]	.29 [.26,.31]	.14 [.12,.17]		.21 [.01,.40]
6. Suppression	5819	2.3	1.57	1.75	0.17	7.18	.17 [.14,.19]	.09 [.07,.12]	.13 [.10,.15]	.28 [.26,.31]	.03 [.01,.06]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.3.1

Descriptive Statistics, Within- and Between-person Correlations of Positive Emotions in Dataset 3: 3-wave longitudinal study (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3
1. Relaxed	12346	6	1.08	2.12	0.92	9.54		.81 [.75,.85]	.64 [.55,.72]
2. Happy	12346	5.87	1.12	1.9	1.24	9.48	.49 [.48,.51]		.78 [.72,.83]
3. Cheerful	12346	5.2	1.11	2.06	0.74	9.24	.36 [.35,.38]	.58 [.57,.59]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.3.2

Descriptive Statistics, Within- and Between-person Correlations of Negative Emotions in Dataset 3: 3-wave longitudinal study (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6
1. Angry	12346	1.19	0.82	1.28	0.09	6.41		.79 [.73,.84]	.60 [.50,.68]	.83 [.79,.87]	.84 [.80,.88]	.58 [.47,.66]
2. Depressed	12346	1.26	0.98	1.2	0.09	5.7	.41 [.40,.43]		.75 [.68,.81]	.85 [.81,.89]	.90 [.86,.92]	.63 [.53,.70]
3. Lonely	12346	1.78	1.33	1.65	0.11	6.93	.21 [.20,.23]	.35 [.34,.37]		.70 [.62,.76]	.72 [.65,.78]	.53 [.42,.62]
4. Anxious	12346	1.03	0.81	0.99	0.08	5.28	.30 [.29,.32]	.38 [.37,.40]	.22 [.21,.24]		.83 [.78,.87]	.63 [.54,.71]
5. Sad	12346	1.31	0.94	1.3	0.09	6.29	.42 [.41,.44]	.59 [.57,.60]	.37 [.36,.39]	.39 [.37,.40]		.61 [.52,.69]
6. Stressed	12346	2.32	1.17	1.96	0.13	7.84	.31 [.29,.32]	.31 [.29,.33]	.18 [.17,.20]	.31 [.30,.33]	.28 [.26,.29]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.3.3

Descriptive Statistics, Within- and Between-person Correlations of Emotion Regulation Strategies in Dataset 3: 3-wave longitudinal study (Leuven)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6
1. Distraction	12346	2.43	1.87	1.8	0.19	7.38		.49 [.38,.59]	.35 [.22,.47]	.42 [.30,.53]	.46 [.34,.56]	.80 [.74,.84]
2. Reappraisal	12346	1.51	1.08	1.29	0.15	6.01	.13 [.12,.15]		.71 [.63,.77]	.60 [.50,.68]	.49 [.38,.59]	.45 [.33,.55]
3. Social Sharing	12346	1.8	1.09	1.72	0.11	7.37	.04 [.03,.06]	.25 [.23,.27]		.48 [.36,.58]	.39 [.26,.50]	.29 [.16,.42]
4. Rumination	12346	1.83	1.35	1.61	0.14	7.01	.13 [.11,.14]	.16 [.14,.17]	.14 [.12,.16]		.68 [.60,.75]	.38 [.25,.49]
5. Worry	12346	3.11	1.7	2.2	0.21	8.17	.12 [.10,.13]	.14 [.12,.16]	.13 [.11,.14]	.25 [.24,.27]		.50 [.38,.59]
6. Suppression	12346	2.01	1.73	1.56	0.19	6.96	.30 [.29,.32]	.11 [.09,.13]	.01 [-.01,.02]	.18 [.16,.20]	.19 [.17,.20]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.4.1

Descriptive Statistics, Within- and Between-person Correlations of Positive Emotions in Dataset 4: Emotion regulation in daily life (Tilburg)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7
1. Energetic	7929	4.09	1.34	1.96	0.83	8.04		.65 [.56,.73]	.79 [.72,.84]	.66 [.56,.73]	.36 [.22,.48]	.77 [.71,.83]	.58 [.47,.67]
2. Content	7934	5.3	1.3	1.91	1.34	8.66	.43 [.41,.45]		.75 [.67,.81]	.49 [.37,.59]	.53 [.42,.63]	.84 [.79,.88]	.59 [.48,.68]
3. Enthusiastic	7944	4.31	1.5	1.91	0.95	8.07	.50 [.49,.52]	.53 [.51,.54]		.64 [.54,.72]	.26 [.11,.39]	.79 [.72,.84]	.65 [.56,.73]
4. Deteremined	7922	3.6	1.46	1.91	0.72	7.72	.42 [.40,.44]	.31 [.29,.33]	.33 [.31,.35]		.28 [.14,.41]	.59 [.48,.67]	.63 [.53,.71]
5. Calm	7929	5.71	1.46	1.93	1.32	8.77	.06 [.04,.08]	.29 [.27,.31]	.09 [.07,.11]	.09 [.07,.11]		.46 [.34,.57]	.28 [.14,.41]
6. Joyful	7919	5.17	1.37	1.85	1.36	8.49	.51 [.49,.52]	.60 [.58,.61]	.57 [.55,.58]	.35 [.33,.37]	.21 [.19,.23]		.59 [.49,.68]
7. Grateful	7904	3.89	1.87	1.84	1	7.99	.33 [.31,.35]	.44 [.42,.46]	.39 [.37,.41]	.30 [.27,.32]	.16 [.14,.18]	.45 [.43,.47]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.4.2

Descriptive Statistics, Within- and Between-person Correlations of Negative Emotions in Dataset 4: Emotion regulation in daily life (Tilburg)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6
1. Irritated	7939	1.68	1.02	1.66	0.24	6.88		.59 [.49,.68]	.74 [.67,.80]	.62 [.53,.71]	.83 [.77,.87]	.61 [.50,.69]
2. Bored	7923	2.24	1.06	1.85	0.28	6.98	.16 [.13,.18]		.46 [.34,.57]	.39 [.26,.51]	.55 [.44,.65]	.36 [.23,.48]
3. Nervous	7909	1.46	1.03	1.34	0.24	5.83	.23 [.21,.25]	.11 [.09,.14]		.79 [.73,.84]	.85 [.80,.89]	.75 [.67,.80]
4. Sad	7898	1.24	1.21	1.07	0.25	4.9	.31 [.29,.33]	.14 [.12,.17]	.29 [.27,.31]		.84 [.78,.88]	.91 [.88,.93]
5. Angry	7886	1.1	0.93	1.11	0.21	5.14	.51 [.49,.52]	.09 [.07,.11]	.25 [.23,.28]	.50 [.49,.52]		.77 [.70,.82]
6. Depressed	7884	1.53	1.31	1.36	0.28	5.74	.34 [.32,.36]	.21 [.19,.23]	.27 [.25,.29]	.62 [.61,.63]	.45 [.43,.47]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.4.3

Descriptive Statistics, Within- and Between-person Correlations of Emotion Regulation Strategies in Dataset 4: Emotion regulation in daily life (Tilburg)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7
1. Distraction	7869	3.14	1.81	2	0.45	7.48		.76 [.70, .82]	.56 [.45, .66]	.56 [.45, .66]	.20 [.06, .34]	.38 [.25, .50]	.42 [.29, .53]
2. Avoidance	7862	2.41	1.59	1.68	0.41	6.74	.30 [.28, .32]		.57 [.46, .66]	.43 [.30, .54]	.11 [-.03, .26]	.32 [.18, .45]	.44 [.32, .55]
3. Rumination	7851	2.1	1.37	1.72	0.33	6.7	.11 [.09, .14]	.13 [.11, .15]		.66 [.56, .73]	.14 [.00, .28]	.70 [.62, .77]	.71 [.63, .78]
4. Problem Solving	7850	2.01	1.34	1.67	0.34	6.58	.15 [.13, .17]	.14 [.12, .16]	.27 [.25, .29]		.30 [.16, .43]	.70 [.62, .77]	.62 [.52, .70]
5. Acceptance	7850	3.64	2.16	1.87	0.74	7.6	.03 [.00, .05]	.00 [-.02, .03]	-.04 [-.06,-.01]	.05 [.02, .07]		.23 [.08, .36]	.17 [.02, .31]
6. Social Sharing	7831	1.71	1.27	1.63	0.24	6.44	.13 [.11, .15]	.07 [.05, .09]	.30 [.28, .32]	.28 [.26, .30]	.05 [.03, .07]		.84 [.79, .88]
7. Co-Brooding	7815	1.25	1.06	1.21	0.19	5.24	.07 [.05, .10]	.07 [.05, .09]	.34 [.32, .36]	.22 [.20, .24]	.03 [.01, .06]	.56 [.54, .57]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.5.1

Descriptive Statistics, Within- and Between-person Correlations of Positive Emotions in Dataset 5: Outside-in (Ghent)

	n	M	SDw	SDb	Min	Max	1	2	3
1. Happy	9838	7.46	2.07	1.9	2.19	9.53		.80 [.75,.85]	.63 [.55,.71]
2. Relaxed	9837	6.88	2.3	2.26	1.44	9.53	.38 [.37,.40]		.68 [.60,.74]
3. Energetic	9838	5.39	2.72	2.54	0.82	9.27	.40 [.38,.42]	.23 [.21,.25]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.5.2

Descriptive Statistics, Within- and Between-person Correlations of Negative Emotions in Dataset 5: Outside-in (Ghent)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6
1. Angry	9838	0.98	1.35	1.55	0.07	6.66		.64 [.55,.71]	.87 [.84,.90]	.88 [.85,.91]	.72 [.65,.78]	.72 [.65,.78]
2. Annoyed	9838	1.88	2.11	1.85	0.08	6.83	.21 [.19,.23]		.61 [.52,.69]	.59 [.49,.67]	.70 [.63,.77]	.74 [.67,.79]
3. Anxious	9836	0.92	1.45	1.25	0.08	5.04	.31 [.30,.33]	.17 [.15,.19]		.83 [.79,.87]	.77 [.70,.82]	.72 [.65,.78]
4. Sad	9838	1.16	1.43	1.69	0.06	6.83	.44 [.43,.46]	.18 [.16,.20]	.31 [.30,.33]		.71 [.63,.77]	.73 [.66,.79]
5. Stressed	9838	2.04	2.16	2.03	0.19	7.6	.23 [.21,.25]	.22 [.20,.24]	.31 [.29,.33]	.23 [.21,.24]		.86 [.82,.89]
6. Uncertain	9838	1.55	2.01	1.56	0.11	6.08	.27 [.25,.29]	.26 [.24,.28]	.42 [.41,.44]	.29 [.27,.30]	.39 [.38,.41]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

Table S3.4.5.3

Descriptive Statistics, Within- and Between-person Correlations of Emotion Regulation Strategies in Dataset 5: Outside-in (Ghent)

	n	M	SDw	SDb	Min	Max	1	2	3	4	5	6	7	8
1. Reappraisal	9838	2.18	2.37	1.79	0.12	6.63		.91 [.89,.93]	.89 [.85,.91]	.66 [.58,.73]	.73 [.66,.79]	.92 [.90,.94]	.92 [.90,.94]	.83 [.78,.87]
2. Distraction	9838	2.36	2.58	1.81	0.17	6.82	.34 [.32,.36]		.90 [.87,.92]	.69 [.62,.76]	.75 [.69,.81]	.91 [.89,.93]	.90 [.87,.92]	.83 [.79,.87]
3. Social Support	9838	2.24	2.47	1.87	0.16	6.67	.25 [.23,.27]	.22 [.21,.24]		.58 [.49,.67]	.76 [.70,.81]	.93 [.91,.95]	.93 [.91,.94]	.92 [.89,.94]
4. Suppression	9838	2.46	2.58	1.92	0.24	7.02	.19 [.17,.21]	.26 [.24,.28]	.05 [.03,.07]		.82 [.77,.86]	.63 [.54,.70]	.61 [.52,.69]	.55 [.45,.64]
5. Rumination	9837	2.52	2.54	1.96	0.26	7.09	.20 [.18,.22]	.22 [.20,.24]	.27 [.26,.29]	.31 [.30,.33]		.73 [.66,.79]	.73 [.66,.78]	.72 [.65,.78]
6. Self-compassion (Support)	9837	2.39	2.62	1.71	0.22	6.6	.30 [.29,.32]	.31 [.29,.32]	.25 [.23,.27]	.19 [.17,.21]	.20 [.18,.22]		.98 [.97,.98]	.89 [.86,.91]
7. Self-compssion (Cheer-up)	9838	2.46	2.67	1.72	0.22	6.64	.32 [.30,.33]	.30 [.28,.32]	.27 [.25,.29]	.16 [.14,.18]	.25 [.24,.27]	.47 [.45,.48]		.90 [.87,.92]
8. Expression	9838	2.18	2.41	1.75	0.24	6.43	.19 [.17,.21]	.16 [.14,.18]	.35 [.33,.37]	.05 [.03,.07]	.23 [.21,.24]	.27 [.25,.29]	.29 [.27,.30]	

Note. SDw: Within-person SD. SDb: Between-person SD. Min: mean of minimum rating. Max: mean of maximum rating. Within-person correlations at lower triangle and between-person correlations at upper triangle. Confidence interval of correlations in squared brackets. All these indices were calculated only in observations with no missingness in relevant ESM items, so the lower n for emotion regulation indices reflected more missing items in constituent ESM items.

SUPPLEMENTAL MATERIALS 4 – MULTILEVEL CONFIRMATORY FACTOR ANALYSIS PER DATASET

We ran Multilevel Confirmatory Factor Analyses (MCFA; see procedures in Eisele et al., (2021) to confirm the factor structure for positive emotions and negative emotions at both within-adolescent and between-adolescent levels. In the MCFA, positive emotion items were loaded on an overall positive emotion factor, negative emotion items were loaded on an overall negative emotion factor. The positive and negative emotion latent factors were allowed to correlate. We inspected model fit with conventional cutoff values (RMSEA < .08, CFI > .90 and TLI > .90; see Schermelleh-Engel et al., 2003). When model fits were unsatisfactory, as in datasets 3, 4, and 5, we allowed residual variance of overlapping items to correlate to improve model fit. In general, model fit at the within-person level was usually worse than at the between-person level. While the TLI is not acceptable in some models, both the RMSEA and CFI are. Overall, positive and negative emotions loaded separately on two factors as indicated with satisfactory fit indices, as shown in Table S3. In other words, it was suitable to take the mean of the positive emotions as a single-factor index, and likewise for negative emotions.

Table S4

Multilevel Confirmatory Factor Analysis per Datasets

Dataset	Within-person					Between-person				
	SFL	X^2	RMSEA	CFI	TLI	SFL	X^2	RMSEA	CFI	TLI
G(F)ood together (Radboud)	.43–.77	359.27	0.06	0.95	0.86	.57–.98	74.06	0.02	0.99	0.98
Emotions in daily life 2011 (Leuven)	.50–.84	231.03	0.07	0.98	0.91	.70–.98	24.69	0.02	> .99	0.99
3-wave longi-tudinal study (Leuven)*	.43–.85	1,025.20	0.06	0.97	0.91	.68–.99	104.47	0.02	> .99	0.99
Emotions in daily life (Tilburg)*	.26–.80	3,011.13	0.08	0.9	0.76	.44–.97	408.03	0.03	0.99	0.97
Outside-in (Ghent)*	.38–.76	876.5	0.06	0.95	0.84	.72–.94	235.35	0.03	0.99	0.96

Note: SFL = standardized factor loadings (all $p < .001$). X^2 = Chi-square. RMSEA = Root Mean Square Error of Approximation. CFI = Comparative Fit Index. TLI = Tucker Lewis Index. When evaluating the fit of the within-person model, a saturated between-person model was specified. When evaluating the between-person model, a saturated within-person was specified. **For datasets 3, 4 and 5, we included correlations between residual variances of overlapping items (e.g., relaxed with stressed) to improve model fit. For the within-person model for dataset 3, we included the correlation between the items "relaxed" and "stressed" at the within-person level. For the within-person model for dataset 4, we included the correlation between the items "angry" and "irritated" and "sad" and "low" at the within-person level. For the within-person model for dataset 5, we included the correlation between the items "angry" and "sad" at the within-person level

SUPPLEMENTAL MATERIALS 5: SPECIFICATION OF WITHIN-PERSON MEDIATION MODEL AND FULL RESULTS OF ALL MULTILEVEL MODELS

Detailed Specifications of the Within-Person Mediation Model 1M

In Model 1M, we examined both the direct and indirect paths. The direct paths included the a-path (from lagged emotion differentiation to emotion regulation variability), the b-path (from emotion regulation variability to emotion intensity), and the c′-path (from lagged emotion differentiation to emotion intensity). The a-path corresponds to the effect analyzed in Model 1A, while the b-path and c′-path reflect how emotion intensity changes directly in response to fluctuations in emotion differentiation and emotion regulation variability. The indirect path in Model 1M, representing the mediation effect, is calculated as the sum of two components: the product of the a-path and b-path, and the covariance between a-path and b-path.

Estimation of the Direct Paths in Model 1M

The direct paths of Model 1M were estimated using the *nlme* package. Model 1M employed a stacked dataset, in which each row of data was split into two rows: one emphasizing the outcome (emotion intensity) and the other the mediator (emotion regulation variability) (Bauer et al., 2006; Bolger & Laurenceau, 2013). In this setup, emotion regulation variability serves as both an outcome in the a-path and a predictor in the b-path. Since we focused on within-person fluctuations, emotion regulation variability had to be modeled as a within-person component, precluding the modeling of its between-person component as an outcome. Consequently, the predictor (emotion differentiation) and outcome (emotion intensity) also had to be specified as within-person components, excluding their between-person components. To align with this approach, the intercepts of the mediator and outcome were fixed to 0 because the within-person components, being person-mean-centered, had zero within-person means. Although this approach allowed us to evaluate within-person mediation accurately (Bolger & Laurenceau, 2013), it prevented us from simultaneously estimating between-person effects within Model 1M, unlike what we did in other models (e.g., Model 1A). However, the three between-person relations among emotion differentiation, emotion regulation variability, and emotion intensity were already evaluated in Models 1A, 1B, 1C, 2A, and 2B.

Model 1M with positive emotion specification encountered an evaluation error for the first-order autocorrelation term on the residual. To check whether estimates deviated when the residual autocorrelation term was removed, we undertook the following steps. First, we ran Model 1M (positive emotion) in a two-step manner, including the autocorrelation term. This involved running Model 1A (positive emotion) and a modified version of Model 2A (positive emotion) with the outcome variable replaced by positive emotion intensity and the covariate positive emotion intensity replaced by lagged positive emotion intensity. Then, we ran these two models (two-step model 1M) again, this time excluding the autocorrelation term on the residual. Finally, we compared the fixed effects of interest (e.g., a-path: positive emotion differentiation → emotion regulation variability, and b-path: emotion regulation variability → positive emotion intensity) between the two-step models with and without the autocorrelation term. The comparisons revealed that the fixed effects for the a-, b-, and c′-paths remained in the same direction and statistical significance. Based on these findings, we proceeded with Model 1M (positive emotion) using the one-step approach described in the main text (i.e., evaluating the a-, b-, and c′-paths in a single multilevel model after the stacking procedure) without including the first-order autocorrelation term on the residual, which allowed Model 1M (positive emotion) to converge. As a result, in this and the subsequent Supplemental Materials, we report the Model 1M (positive emotion) results evaluated without specifying the first-order autocorrelation term on the residual.

All within-person mediation models (whether for positive or negative emotions and across varied specifications in sensitivity analyses) produced warnings about singularity precision, indicating that some random slopes were estimated as zero or that correlations between them were approaching 1 or -1 (Bates, Kliegl, et al., 2015). To address this, we first simplified the models by removing random effects for variables not central to our primary interests (e.g., from lagged emotion intensity to emotion intensity). However, the singularity warnings persisted. Upon inspecting the outputs from both the full models and the simplified models without additional random slopes, we found that the warnings were caused by correlations between dataset-level random effects approaching 1 or -1. At the person-level, however, none of the random effects were estimated as zero, nor were any correlations between them near 1 or -1. Given that our primary focus is on interpreting person-level results, we deemed it acceptable to proceed with the estimates despite the presence of singularity precision warnings.

Estimation of the Indirect Path of Model 1M

Making use of the estimates from *nlme*, we can calculate the indirect path as the sum of two components: product of the a-path and b-path, and covariance of person-level random effects of the a-path and b-path. To further obtain the confidence interval of the indirect path, we made use of the Monte Carlo script by Preacher & Selig, (2010). To prepare for this, we used the *lme4* package (Bates, Mächler, et al., 2015) in addition to *nlme* which we have used for evaluating other models. Both the *nlme* and *lme4* packages can evaluate three-level models, grouping measurements within adolescents and adolescents within datasets. Apart from *nlme* and *lme4*, other software options exist, namely the *brms* package (see Ram, 2022 for tutorial) and Mplus, a proprietary software (see McNeish & MacKinnon, 2022 for tutorial). However, unlike *nlme* and *lme4*, *brms* and Mplus can not yet simultaneously handle three-level nested structure and estimation of within-person mediation. So, we could only proceed with the *nlme* and *lme4* packages.

For models other than Model 1M, we primarily used the *nlme* package, as it supports the inclusion of a first-order autocorrelation term on the residual, which *lme4* does not. However, only *lme4* has compatible resources for extracting the asymptotic covariance of random effects for two paths, an estimate needed for accurately assessing the confidence interval of the mediation effect (see (Ram, 2017) for an overview). This estimate affects the dispersion of the Monte Carlo resampled indirect effect: the larger it is, the wider the resample distribution's bell curve.

It is still possible to produce a confidence interval without this estimate using *nlme* results, but the interval will be liberal. This means that even if the interval does not include zero, we cannot be certain this would remain the case if the asymptotic covariance of random effects were included. Conversely, if the interval does include zero, we can be confident it will continue to include zero even when the missing estimate is added.

In summary, each package has distinct advantages and disadvantages. The *nlme* results come from better-specified models but provide a liberal confidence interval, which is not reliable for rejecting the null hypothesis of no within-person mediation. Conversely, *lme4* can produce a confidence interval capable of rejecting this null hypothesis, but it does so based on model estimates evaluated without the first-order autocorrelation residual term. For this exploratory research question, we computed the 95% confidence intervals for mediation using the Monte Carlo script by Preacher & Selig (2010) with results from both packages. To ensure robustness of our results, we reported the more conservative results between the two sets. For example, if one set gave an interval that crossed zero but the other set did not, we reported the set that crossed zero.

Before using *lme4* results, it was necessary to assess whether *lme4* results were similar as those from *nlme*. Therefore, we compared the fixed effects of interest (e.g., a-path: emotion differentiation → emotion regulation variability, and b-path: emotion regulation variability → emotion intensity) in Model 1M as estimated by both packages. The fixed effects showed the same direction and statistical significance in both *nlme* and *lme4*.

We initially planned to use the *lme4* package to reevaluate models under various specifications detailed in Supplemental Materials 6 and 7. However, under those sensitivity analysis specifications, the *lme4* estimates showed very large deviations from those of *nlme* and encountered other errors (see Supplemental Materials 6 and 7 for details), making it impractical to conduct sensitivity analyses as extensively as we did for the direct paths in Model 1M and for estimates in other models without within-person mediation.

Table S5

Full Multilevel Model Results

	Negative Emotions *b* [95% CI]	**Positive Emotions *b* [95% CI]**
Outcome: Emotion regulation variability (Model 1A)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		
Lagged emotion differentiation	**-0.009 [-0.014, -0.005]**	**-0.009 [-0.014, -0.004]**
Lagged emotion intensity	-0.018 [-0.043, 0.007]	-0.005 [-0.017, 0.007]
Emotion regulation intensity	0.295 [-0.283, 0.872]	0.280 [-0.276, 0.837]
Time trend	**-0.003 [-0.004, -0.003]**	**-0.003 [-0.004, -0.002]**
Between-person (time-invariant)		
Intercept	**3.895 [2.773, 5.018]**	**4.056 [2.819, 5.294]**
Emotion differentiation	0.068 [-0.072, 0.207]	-0.053 [-0.258, 0.153]
Emotion intensity	-0.023 [-0.128, 0.083]	**-0.107 [-0.181, -0.034]**
Emotion regulation intensity	**-0.552 [-0.629, -0.475]**	**-0.561 [-0.631, -0.492]**
Age	-0.005 [-0.063, 0.054]	-0.012 [-0.077, 0.053]
Gender (female = 1, male = 0)	**0.412 [0.188, 0.637]**	**0.347 [0.120, 0.575]**
Outcome: Strategy switching (Model 1B)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		
Endorsement change	**-0.436 [-0.576, -0.296]**	**-0.437 [-0.575, -0.300]**
Lagged emotion differentiation	**-0.004 [-0.007, -0.002]**	**-0.004 [-0.007, 0.000]**
Lagged emotion intensity	-0.010 [-0.025, 0.005]	-0.002 [-0.013, 0.009]
Emotion regulation intensity	**-0.102 [-0.153, -0.051]**	**-0.102 [-0.149, -0.055]**
Time trend	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.002, -0.001]**
Between-person (time-invariant)		
Intercept	**0.978 [0.346, 1.610]**	**0.993 [0.317, 1.670]**
Endorsement change	0.017 [-0.027, 0.061]	0.008 [-0.036, 0.052]
Emotion differentiation	**0.156 [0.086, 0.226]**	0.017 [-0.089, 0.123]
Emotion intensity	0.032 [-0.022, 0.085]	-0.035 [-0.073, 0.002]
Emotion regulation intensity	0.015 [-0.029, 0.058]	0.011 [-0.029, 0.052]
Age	**0.032 [0.002, 0.061]**	0.031 [-0.001, 0.064]
Gender (female = 1, male = 0)	**0.138 [0.026, 0.250]**	**0.127 [0.012, 0.242]**
Outcome: Endorsement change (Model 1C)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		
Strategy switching	0.312 [-1.140, 1.764]	0.302 [-1.135, 1.740]
Lagged emotion differentiation	**-0.008 [-0.012, -0.004]**	**-0.007 [-0.012, -0.003]**
Lagged emotion intensity	**-0.017 [-0.034, 0.000]**	-0.004 [-0.012, 0.004]
Emotion regulation intensity	0.054 [-0.233, 0.341]	0.058 [-0.228, 0.344]
Time trend	**-0.002 [-0.003, -0.002]**	**-0.002 [-0.003, -0.001]**
Between-person (time-invariant)		
Intercept	**2.427 [1.550, 3.304]**	**2.523 [1.653, 3.392]**
Strategy switching	**-0.234 [-0.318, -0.150]**	**-0.238 [-0.322, -0.154]**

Table S5

Full Multilevel Model Results (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Emotion differentiation	-0.082 [-0.184, 0.019]	**-0.148 [-0.296, 0.000]**
Emotion intensity	-0.072 [-0.148, 0.004]	0.025 [-0.028, 0.079]
Emotion regulation intensity	**-0.677 [-0.733, -0.621]**	**-0.696 [-0.746, -0.645]**
Age	-0.009 [-0.056, 0.039]	-0.014 [-0.061, 0.033]
Gender (female = 1, male = 0)	**0.215 [0.054, 0.376]**	**0.203 [0.041, 0.366]**
Within-person mediation (Model 1M)	N = 756, n = 52003	N = 755, n = 51991
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.013 [-0.018, -0.008]**	**-0.014 [-0.020, -0.008]**
Lagged emotion intensity → emotion regulation variability	-0.029 [-0.085, 0.026]	-0.005 [-0.025, 0.016]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.073 [0.038, 0.108]**	**-0.049 [-0.091, -0.006]**
Emotion regulation intensity → emotion intensity	**0.234 [0.166, 0.303]**	**-0.102 [-0.187, -0.018]**
Lagged emotion intensity → emotion intensity	**0.259 [0.204, 0.315]**	**0.300 [0.249, 0.351]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.008 [0.003, 0.013]**	**-0.016 [-0.026, -0.006]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.003, -0.001]**
Mediation (sum of covariance and product of a- and b-path)	-0.000 [-0.001, 0.000]	-0.000 [-0.001, 0.001]
Within-person mediation (Model 1M) with person-level emotion differentiation as a moderator to a-path and b-path	N = 756, n = 52003	N = 755, n = 51991
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.015 [-0.020, -0.010]**	**-0.016 [-0.022, -0.010]**
Lagged emotion intensity → emotion regulation variability	-0.031 [-0.088, 0.026]	-0.005 [-0.026, 0.016]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.074 [0.038, 0.110]**	**-0.048 [-0.090, -0.006]**
Emotion regulation intensity → emotion intensity	**0.236 [0.167, 0.306]**	**-0.103 [-0.188, -0.018]**
Lagged emotion intensity → emotion intensity	**0.259 [0.201, 0.317]**	**0.301 [0.249, 0.352]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.008 [0.003, 0.014]**	**-0.016 [-0.026, -0.006]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.003, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by between-person emotion differentiation	**-0.006 [-0.010, -0.002]**	-0.010 [-0.020, 0.000]

Table S5

Full Multilevel Model Results (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Emotion regulation variability → emotion intensity (b-path), moderated by between-person emotion differentiation	**-0.034 [-0.057, -0.010]**	0.046 [-0.002, 0.094]
Outcome: Emotion differentiation (Model 2A)	N = 751, n = 25830	N = 750, n = 25834
Within-person (time-varying)		
Emotion regulation variability	**-0.514 [-0.731, -0.296]**	**-0.276 [-0.496, -0.057]**
Lagged emotion differentiation	**-0.020 [-0.032, -0.007]**	**0.031 [0.001, 0.062]**
Emotion intensity	**-3.884 [-4.989, -2.779]**	**0.519 [0.206, 0.832]**
Emotion regulation intensity	-0.026 [-0.110, 0.058]	**-0.150 [-0.246, -0.055]**
Time trend	**-0.006 [-0.008, -0.004]**	**0.004 [0.003, 0.006]**
Between-person (time-invariant)		
Intercept	**-1.225 [-1.874, -0.576]**	-0.547 [-1.221, 0.127]
Emotion regulation variability	-0.035 [-0.072, 0.001]	-0.012 [-0.039, 0.015]
Emotion intensity	**-0.238 [-0.296, -0.180]**	**0.035 [0.005, 0.065]**
Emotion regulation intensity	-0.043 [-0.087, 0.001]	-0.014 [-0.044, 0.015]
Age	**-0.046 [-0.081, -0.011]**	**-0.069 [-0.100, -0.037]**
Gender (female = 1, male = 0)	0.047 [-0.074, 0.168]	**-0.149 [-0.239, -0.058]**
Outcome: Emotion differentiation (Model 2B)	N = 751, n = 25830	N = 750, n = 25834
Within-person (time-varying)		
Strategy switching	**-0.432 [-0.730, -0.133]**	**-0.306 [-0.525, -0.086]**
Endorsement change	**-0.550 [-0.771, -0.328]**	**-0.262 [-0.480, -0.043]**
Lagged emotion differentiation	**-0.018 [-0.030, -0.006]**	**0.031 [0.000, 0.062]**
Emotion intensity	**-3.887 [-5.009, -2.764]**	**0.519 [0.205, 0.833]**
Emotion regulation intensity	-0.035 [-0.121, 0.051]	**-0.149 [-0.243, -0.054]**
Time trend	**-0.006 [-0.008, -0.004]**	**0.004 [0.003, 0.006]**
Between-person (time-invariant)		
Intercept	**-1.264 [-1.921, -0.606]**	-0.558 [-1.234, 0.119]
Strategy switching	0.055 [-0.008, 0.118]	-0.004 [-0.052, 0.044]
Endorsement change	**-0.091 [-0.140, -0.042]**	-0.018 [-0.055, 0.019]
Emotion intensity	**-0.239 [-0.297, -0.181]**	**0.034 [0.004, 0.064]**
Emotion regulation intensity	**-0.068 [-0.114, -0.022]**	-0.017 [-0.049, 0.015]
Age	**-0.044 [-0.079, -0.009]**	**-0.068 [-0.099, -0.037]**
Gender (female = 1, male = 0)	0.034 [-0.086, 0.153]	**-0.148 [-0.238, -0.057]**

Note. Significant effects are displayed in bold. n: number of ESM assessments; N: number of adolescents; b: unstandardized effect; CI: confidence interval. In Model 1M, n is doubled because of how data have undergone the stacking preparation step.

SUPPLEMENTAL MATERIALS 6: SENSITIVITY ANALYSES USING THE SUCCESSIVE APPROACH TO CALCULATE BRAY-CURTIS DISSIMILARITY

In the main analyses, we calculated emotion regulation variability as Bray-Curtis dissimilarity by comparing the moment of interest with all other moments the same individual reported, which is known as the all-moment comparison approach. An alternative approach to calculating Bray-Curtis dissimilarity is by the successive temporal comparison which compares the moment of interest with the previous moment. This approach of calculation is not available if such previous moments have missingness, but the all-moment comparison approach can still compute the dissimilarity as long as there are at least two observations. As sensitivity analyses, we ran the same analyses with the successive temporal comparison approach. As shown in Table S6, the momentary reciprocal hindrance between negative emotion differentiation and emotion regulation variability was also seen when emotion regulation variability was calculated in the successive temporal comparison approach. In terms of individual differences, similar to our main findings, there were no significant associations between negative emotion differentiation and emotion regulation variability (model 2A). In summary, our confirmatory hypotheses about the relations between negative emotion differentiation and emotion regulation variability were robust.

As for the sensitivity analyses of exploratory models on two emotion regulation variability subcomponents, model 1B, 1C, and 2B showed similar findings that there were momentary reciprocal hinderance between negative emotion differentiation and emotion regulation variability, except that the strategy switching subsequent no longer significantly predict changes in emotion differentiation in the subsequent moment (model 2B). In terms of individual difference, interestingly, in addition to the between-person negative association between negative emotion differentiation and endorsement change, there was a positive association between negative emotion differentiation and strategy switching (model 2B). In other words, the degree to which participants switched from one strategy to another on average was positively related to their baseline negative emotion differentiation. In summary, the relations between negative emotion differentiation and emotion regulation variability subcomponents were also largely robust.

Sensitivity analyses of exploratory models on positive emotion differentiation showed that relations between positive emotion differentiation and emotion regulation variability were less robust than those between negative emotion differentiation and emotion regulation variability. Higher positive emotion differentiation preceded lower emotion regulation variability (model 1A) and specifically lower endorsement change (model 1C). Other than these, no other within-person temporal relations or between-person relations were found (model 1B, 2A, and 2B).

In the sensitivity analyses of the exploratory within-person mediation models (Model 1M), the direct paths results were consistent in direction and statistical significance with our main analyses. As a preparatory step for evaluating the indirect path, we reanalyzed the model using the *lme4* package under the successive temporal comparison approach specification. However, the lmer estimates for the b-path and c'-path in Model 1M (negative emotion) were in the opposite direction compared to our main analyses. This discrepancy may stem from the exclusion of the autocorrelated residual term, which was based on a lag-one temporal relation similar to the successive temporal comparison and becomes highly influential in the successive temporal comparison approach to operationalizing emotion regulation variability. Consequently, we were unable to estimate the confidence intervals for the indirect paths.

Table S6

Multilevel Model Results (Using the successive approach to calculate Bray-Curtis dissimilarity)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Outcome: Emotion regulation variability (Model 1A)	N = 678, n = 25522	N = 677, n = 25502
Within-person (time-varying)		
Lagged emotion differentiation	**-0.017 [-0.025, -0.010]**	**-0.021 [-0.039, -0.003]**
Lagged emotion intensity	-0.031 [-0.198, 0.136]	-0.006 [-0.051, 0.038]
Emotion regulation intensity	0.027 [-0.322, 0.376]	0.017 [-0.328, 0.361]
Time trend	**-0.006 [-0.008, -0.005]**	**-0.006 [-0.008, -0.004]**
Between-person (time-invariant)		
Intercept	**3.330 [2.293, 4.368]**	**3.145 [2.043, 4.247]**
Emotion differentiation	0.078 [-0.047, 0.204]	-0.020 [-0.214, 0.174]
Emotion intensity	0.014 [-0.083, 0.110]	-0.058 [-0.125, 0.009]
Emotion regulation intensity	**-0.504 [-0.573, -0.435]**	**-0.508 [-0.571, -0.445]**
Age	-0.002 [-0.053, 0.049]	0.008 [-0.047, 0.064]
Gender (female = 1, male = 0)	**0.240 [0.041, 0.440]**	**0.241 [0.036, 0.447]**
Outcome: Strategy switching (Model 1B)	N = 678, n = 25522	N = 677, n = 25502
Within-person (time-varying)		
Endorsement change	**-0.382 [-0.488, -0.275]**	**-0.380 [-0.484, -0.276]**
Lagged emotion differentiation	**-0.009 [-0.016, -0.002]**	-0.007 [-0.019, 0.005]
Lagged emotion intensity	-0.027 [-0.117, 0.062]	-0.007 [-0.041, 0.026]
Emotion regulation intensity	-0.071 [-0.154, 0.013]	-0.073 [-0.164, 0.018]
Time trend	**-0.004 [-0.005, -0.003]**	**-0.004 [-0.005, -0.002]**
Between-person (time-invariant)		
Intercept	**1.513 [1.035, 1.991]**	**1.470 [0.995, 1.944]**
Endorsement change	**0.092 [0.056, 0.128]**	**0.090 [0.054, 0.126]**
Emotion differentiation	**0.098 [0.044, 0.152]**	0.070 [-0.016, 0.155]

Table S6

Multilevel Model Results (Using the successive approach to calculate Bray-Curtis dissimilarity) (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Emotion intensity	0.000 [-0.047, 0.047]	-0.017 [-0.045, 0.011]
Emotion regulation intensity	0.005 [-0.030, 0.040]	-0.008 [-0.039, 0.024]
Age	-0.002 [-0.018, 0.014]	0.001 [-0.016, 0.017]
Gender (female = 1, male = 0)	0.085 [-0.001, 0.171]	0.084 [-0.003, 0.170]
Outcome: Endorsement change (Model 1C)	N = 678, n = 25522	N = 677, n = 25502
Within-person (time-varying)		
Strategy switching	**-0.487 [-0.525, -0.449]**	**-0.486 [-0.522, -0.451]**
Lagged emotion differentiation	**-0.015 [-0.022, -0.008]**	**-0.020 [-0.036, -0.005]**
Lagged emotion intensity	-0.040 [-0.177, 0.096]	0.004 [-0.029, 0.037]
Emotion regulation intensity	-0.017 [-0.303, 0.270]	-0.027 [-0.319, 0.264]
Time trend	**-0.005 [-0.007, -0.004]**	**-0.005 [-0.007, -0.003]**
Between-person (time-invariant)		
Intercept	**1.446 [0.725, 2.167]**	**1.507 [0.788, 2.227]**
Strategy switching	**0.108 [0.036, 0.180]**	**0.090 [0.018, 0.162]**
Emotion differentiation	-0.011 [-0.096, 0.073]	-0.074 [-0.203, 0.055]
Emotion intensity	-0.052 [-0.119, 0.014]	-0.008 [-0.052, 0.035]
Emotion regulation intensity	**-0.325 [-0.374, -0.276]**	**-0.347 [-0.391, -0.304]**
Age	0.022 [-0.016, 0.060]	0.019 [-0.019, 0.056]
Gender (female = 1, male = 0)	0.089 [-0.042, 0.219]	0.088 [-0.044, 0.220]
Within-person mediation (Model 1M)	N = 682, n = 51338	N = 681, n = 51305
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.027 [-0.035, -0.019]**	**-0.027 [-0.040, -0.013]**
Lagged emotion intensity → emotion regulation variability	-0.110 [-0.312, 0.092]	0.004 [-0.054, 0.062]
Time trend → emotion regulation variability	**-0.006 [-0.008, -0.005]**	**-0.006 [-0.007, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.026 [0.020, 0.032]**	-0.013 [-0.028, 0.003]
Emotion regulation intensity → emotion intensity	**0.257 [0.196, 0.318]**	**-0.127 [-0.225, -0.029]**
Lagged emotion intensity → emotion intensity	**0.265 [0.243, 0.287]**	**0.310 [0.253, 0.368]**
Lagged emotion differentiation → emotion intensity (c′-path)	**0.009 [0.006, 0.012]**	**-0.018 [-0.028, -0.008]**
Time trend → emotion intensity	**-0.002 [-0.003, -0.001]**	**-0.002 [-0.003, -0.001]**

Table S6

Multilevel Model Results (Using the successive approach to calculate Bray-Curtis dissimilarity) (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Within-person mediation (Model 1M) with person-level emotion differentiation as a moderator to a-path and b-path	N = 682, n = 51338	N = 681, n = 51305
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.031 [-0.040, -0.022]**	**-0.032 [-0.055, -0.010]**
Lagged emotion intensity → emotion regulation variability	-0.111 [-0.356, 0.134]	0.008 [-0.047, 0.062]
Time trend → emotion regulation variability	**-0.006 [-0.008, -0.005]**	**-0.006 [-0.007, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.027 [0.021, 0.033]**	-0.012 [-0.028, 0.003]
Emotion regulation intensity → emotion intensity	**0.255 [0.186, 0.324]**	**-0.127 [-0.228, -0.025]**
Lagged emotion intensity → emotion intensity	**0.268 [0.193, 0.344]**	**0.311 [0.252, 0.370]**
Lagged emotion differentiation → emotion intensity (c′-path)	**0.009 [0.005, 0.013]**	**-0.018 [-0.029, -0.008]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.003, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by between-person emotion differentiation	**-0.014 [-0.022, -0.006]**	-0.016 [-0.038, 0.007]
Emotion regulation variability → emotion intensity (b-path), moderated by between-person emotion differentiation	0.000 [-0.007, 0.006]	0.015 [-0.002, 0.032]
Outcome: Emotion differentiation (Model 2A)	N = 678, n = 25510	N = 673, n = 25402
Within-person (time-varying)		
Emotion regulation variability	**-0.087 [-0.135, -0.038]**	0.005 [-0.011, 0.021]
Lagged emotion differentiation	**-0.022 [-0.034, -0.009]**	0.026 [-0.006, 0.057]
Emotion intensity	**-4.415 [-5.598, -3.233]**	**0.671 [0.422, 0.920]**
Emotion regulation intensity	0.074 [-0.006, 0.154]	-0.040 [-0.093, 0.013]
Time trend	**-0.005 [-0.008, -0.003]**	**0.004 [0.002, 0.006]**
Between-person (time-invariant)		
Intercept	**-1.611 [-2.247, -0.975]**	-0.077 [-0.691, 0.537]
Emotion regulation variability	-0.017 [-0.057, 0.024]	-0.006 [-0.036, 0.023]
Emotion intensity	**-0.238 [-0.299, -0.177]**	**0.035 [0.004, 0.065]**
Emotion regulation intensity	**-0.047 [-0.092, -0.001]**	-0.011 [-0.041, 0.018]
Age	-0.029 [-0.064, 0.006]	**-0.068 [-0.099, -0.036]**
Gender (female = 1, male = 0)	0.068 [-0.058, 0.193]	**-0.157 [-0.248, -0.065]**
Outcome: Emotion differentiation (Model 2B)	N = 678, n = 25510	N = 673, n = 25402

Table S6

Multilevel Model Results (Using the successive approach to calculate Bray-Curtis dissimilarity) (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Within-person (time-varying)		
Strategy switching	-0.065 [-0.145, 0.014]	0.017 [-0.004, 0.039]
Endorsement change	**-0.099 [-0.147, -0.051]**	0.000 [-0.017, 0.017]
Lagged emotion differentiation	**-0.022 [-0.035, -0.009]**	0.025 [-0.006, 0.057]
Emotion intensity	**-4.399 [-5.535, -3.264]**	**0.672 [0.423, 0.921]**
Emotion regulation intensity	0.072 [-0.005, 0.149]	-0.040 [-0.093, 0.014]
Time trend	**-0.005 [-0.008, -0.003]**	**0.004 [0.002, 0.006]**
Between-person (time-invariant)		
Intercept	**-1.659 [-2.318, -1.001]**	-0.100 [-0.711, 0.512]
Strategy switching	0.069 [-0.003, 0.141]	0.019 [-0.034, 0.072]
Endorsement change	**-0.081 [-0.141, -0.021]**	-0.025 [-0.068, 0.019]
Emotion intensity	**-0.242 [-0.303, -0.181]**	**0.035 [0.005, 0.065]**
Emotion regulation intensity	**-0.067 [-0.115, -0.019]**	-0.018 [-0.051, 0.014]
Age	-0.026 [-0.062, 0.010]	**-0.066 [-0.098, -0.035]**
Gender (female = 1, male = 0)	0.060 [-0.065, 0.185]	**-0.157 [-0.249, -0.066]**

Note. Significant effects are displayed in bold. n: number of ESM assessments; N: number of adolescents; b: unstandardized effect; CI: confidence interval. In Model 1M, n is doubled because of how data have undergone the stacking preparation step.

SUPPLEMENTAL MATERIALS 7: SENSITIVITY ANALYSES ON THE POTENTIAL INFLUENCE OF ZERO NEGATIVE EMOTION INTENSITY AND ZERO EMOTION REGULATION INTENSITY

Supplemental Materials 3 indicated that negative emotion intensity and emotion regulation intensity may experience some extent of floor effects. To address whether the presence of zero-intensity moments (where all negative emotions or regulation strategies were rated zero) confounded our main findings, we conducted sensitivity analyses as described in the below paragraphs. Positive emotions were excluded from these analyses, as descriptive statistics did not indicate the presence of floor effects in them.

We first created binary variables to indicate the presence of zero-intensity moments for negative emotions or emotion regulation strategies (first half of Table S7). These binary variables were multiplied by the within-person components of the independent variables in all models (e.g., emotion differentiation in Model 1A) to generate within-person moderators. All models (1A to 2B, for both positive and negative emotions) were then reanalyzed with the binary variables and within-person moderators included. Random effects for these within-person moderators correspondingly specified.

We ran a second set of sensitivity analyses using the within-person components of negative emotion intensity and emotion regulation intensity from our original models (second half of Table S7). These intensity variables were multiplied by the independent variables (e.g., the product of within-person negative emotion intensity and negative emotion differentiation in Model 1A) to create new within-person moderators. The analyses for all models (1A to 2B) were repeated with these continuous moderators added, again with random effects for these within-person moderators correspondingly specified.

Across both sets of analyses, the main effects of interest (e.g., emotion differentiation in Model 1A) generally remained consistent in direction and statistical significance. An exception arose in Model 1M with binary zero-intensity moderators, where the a-path (emotion differentiation to regulation variability) and b-path (regulation variability to emotion intensity) were no longer significant. However, in Model 1M with continuous intensity moderators, the direct paths remained significant, consistent with the main analyses. These findings indicate that our results are generally robust against the presence of zero intensity in negative emotions and emotion regulation strategies.

As a preparatory step for evaluating the indirect path in Model 1M, we reanalyzed Model 1M with the aforementioned specifications using the *lme4* package. However, we encountered convergence issue in the binary moderator model, making us unable to obtain any estimates. As for the continuous moderator model, extraction of asymptotic covariance of random effects encountered an error as the model became too complex for evaluating so. Consequently, we were unable to estimate the confidence intervals for the indirect paths.

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity

	Negative Emotions *b* *[95% CI]*
Presence of zero emotion (regulation) intensity as moderator	
Outcome: Emotion regulation variability (Model 1A)	N = 752, n = 25867
Within-person (time-varying)	
Lagged emotion differentiation	**-0.009 [-0.013, -0.005]**
Lagged emotion intensity	-0.021 [-0.046, 0.004]
Emotion regulation intensity	0.290 [-0.286, 0.866]
Time trend	**-0.003 [-0.004, -0.002]**
When the intensity of all emotions is rated zero → emotion regulation variability	0.032 [-0.053, 0.117]
Lagged emotion differentiation, when the intensity of all emotions is rated zero	**-0.056 [-0.107, -0.005]**
Between-person (time-invariant)	
Intercept	**3.948 [2.812, 5.084]**
Emotion differentiation	0.056 [-0.083, 0.195]
Emotion intensity	-0.032 [-0.137, 0.074]
Emotion regulation intensity	**-0.555 [-0.632, -0.479]**
Age	-0.007 [-0.066, 0.053]
Gender (female = 1, male = 0)	**0.410 [0.186, 0.633]**
Outcome: Strategy switching (Model 1B)	N = 752, n = 25867
Within-person (time-varying)	
Endorsement change	**-0.435 [-0.575, -0.294]**
Lagged emotion differentiation	**-0.004 [-0.006, -0.001]**
Lagged emotion intensity	-0.010 [-0.024, 0.005]
Emotion regulation intensity	**-0.103 [-0.153, -0.053]**
Time trend	**-0.002 [-0.002, -0.001]**
When the intensity of all emotions is rated zero → emotion regulation variability	0.012 [-0.044, 0.068]
Lagged emotion differentiation, when the intensity of all emotions is rated zero	-0.018 [-0.047, 0.011]
Between-person (time-invariant)	
Intercept	**0.912 [0.283, 1.540]**
Endorsement change	0.014 [-0.029, 0.058]
Emotion differentiation	**0.151 [0.081, 0.222]**
Emotion intensity	0.029 [-0.025, 0.083]
Emotion regulation intensity	0.013 [-0.031, 0.056]

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* *[95% CI]*
Age	**0.036 [0.006, 0.065]**
Gender (female = 1, male = 0)	**0.139 [0.027, 0.251]**
Outcome: Endorsement change (Model 1C)	N = 752, n = 25867
Within-person (time-varying)	
Strategy switching	0.311 [-1.121, 1.743]
Lagged emotion differentiation	**-0.007 [-0.011, -0.004]**
Lagged emotion intensity	-0.015 [-0.032, 0.001]
Emotion regulation intensity	0.057 [-0.227, 0.341]
Time trend	**-0.002 [-0.003, -0.002]**
When the intensity of all emotions is rated zero → emotion regulation variability	0.048 [-0.018, 0.114]
Lagged emotion differentiation, when the intensity of all emotions is rated zero	-0.052 [-0.106, 0.003]
Between-person (time-invariant)	
Intercept	**2.536 [1.690, 3.382]**
Strategy switching	**-0.239 [-0.323, -0.156]**
Emotion differentiation	-0.088 [-0.190, 0.014]
Emotion intensity	-0.074 [-0.150, 0.001]
Emotion regulation intensity	**-0.681 [-0.737, -0.625]**
Age	-0.015 [-0.061, 0.031]
Gender (female = 1, male = 0)	**0.219 [0.059, 0.378]**
Within-person mediation (Model 1M)	N = 756, n = 52003
Within-person (time-varying)	
When the intensity of all emotions is rated zero → emotion regulation variability	0.156 [-0.048, 0.359]
When the intensity of all emotion regulation strategies is rated zero → emotion intensity	**1.124 [0.337, 1.911]**
Lagged emotion differentiation → emotion regulation variability (a-path)	0.001 [-0.030, 0.033]
Lagged emotion intensity → emotion regulation variability	0.192 [-0.194, 0.579]
Time trend → emotion regulation variability	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	0.002 [-0.036, 0.041]
Emotion regulation intensity → emotion intensity	**0.241 [0.174, 0.308]**
Lagged emotion intensity → emotion intensity	**0.342 [0.253, 0.430]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.012 [0.002, 0.022]**
Time trend → emotion intensity	**-0.002 [-0.003, -0.002]**
Lagged emotion differentiation → emotion regulation variability (a-path), when the intensity of all emotions is rated zero	0.159 [-0.029, 0.347]
Emotion regulation variability → emotion intensity (b-path), when the intensity of all emotion regulation strategies is rated zero	**-1.044 [-1.361, -0.726]**

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* *[95% CI]*
Within-person mediation (Model 1M) with person-level emotion differentiation as a moderator to a-path and b-path	N = 756, n = 52003
Within-person (time-varying)	
When the intensity of all emotions is rated zero → emotion regulation variability	0.157 [-0.055, 0.368]
When the intensity of all emotion regulation strategies is rated zero → emotion intensity	**1.128 [0.300, 1.956]**
Lagged emotion differentiation → emotion regulation variability (a-path)	-0.002 [-0.033, 0.030]
Lagged emotion intensity → emotion regulation variability	0.184 [-0.216, 0.584]
Time trend → emotion regulation variability	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	0.004 [-0.041, 0.049]
Emotion regulation intensity → emotion intensity	**0.242 [0.168, 0.316]**
Lagged emotion intensity → emotion intensity	**0.341 [0.247, 0.435]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.013 [0.001, 0.024]**
Time trend → emotion intensity	**-0.002 [-0.003, -0.002]**
Lagged emotion differentiation → emotion regulation variability (a-path), when the intensity of all emotions is rated zero	0.151 [-0.051, 0.352]
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by between-person emotion differentiation	**-0.013 [-0.019, -0.007]**
Emotion regulation variability → emotion intensity (b-path), when the intensity of all emotion regulation strategies is rated zero	**-1.040 [-1.363, -0.717]**
Emotion regulation variability → emotion intensity (b-path), moderated by between-person emotion differentiation	**-0.034 [-0.059, -0.009]**
Outcome: Emotion differentiation (Model 2A)	N = 751, n = 25830
Within-person (time-varying)	
Emotion regulation variability	**-0.510 [-0.727, -0.292]**
Lagged emotion differentiation	**-0.019 [-0.032, -0.005]**
Emotion intensity	**-3.900 [-5.118, -2.682]**
Emotion regulation intensity	-0.037 [-0.133, 0.058]
Time trend	**-0.006 [-0.008, -0.003]**
When the intensity of all emotion regulation strategies is rated zero → emotion intensity	-0.412 [-0.883, 0.059]
Emotion regulation variability, when the intensity of all emotion regulation strategies is rated zero	0.205 [-0.040, 0.450]
Between-person (time-invariant)	
Intercept	**-1.014 [-1.701, -0.327]**
Emotion regulation variability	**-0.059 [-0.098, -0.019]**

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* [95% CI]
Emotion intensity	**-0.260 [-0.314, -0.205]**
Emotion regulation intensity	**-0.123 [-0.175, -0.071]**
Age	**-0.053 [-0.089, -0.017]**
Gender (female = 1, male = 0)	0.040 [-0.073, 0.153]
Outcome: Emotion differentiation (Model 2B)	N = 751, n = 25830
Within-person (time-varying)	
Strategy switching	**-0.447 [-0.689, -0.205]**
Endorsement change	**-0.545 [-0.782, -0.307]**
Lagged emotion differentiation	**-0.016 [-0.031, -0.002]**
Emotion intensity	**-3.873 [-5.187, -2.559]**
Emotion regulation intensity	-0.043 [-0.148, 0.063]
Time trend	**-0.006 [-0.008, -0.004]**
When the intensity of all emotion regulation strategies is rated zero → emotion intensity	-0.091 [-0.646, 0.464]
Endorsement change, when the intensity of all emotion regulation strategies is rated zero	**0.323 [0.047, 0.598]**
Strategy switching, when the intensity of all emotion regulation strategies is rated zero	**0.594 [0.232, 0.956]**
Between-person (time-invariant)	
Intercept	**-0.927 [-1.595, -0.259]**
Strategy switching	-0.029 [-0.095, 0.037]
Endorsement change	**-0.069 [-0.127, -0.012]**
Emotion intensity	**-0.268 [-0.322, -0.213]**
Emotion regulation intensity	**-0.109 [-0.164, -0.054]**
Age	**-0.060 [-0.095, -0.025]**
Gender (female = 1, male = 0)	0.037 [-0.075, 0.150]
Within-person emotion (regulation) intensity as moderator	
Outcome: Emotion regulation variability (Model 1A)	N = 752, n = 25867
Within-person (time-varying)	
Lagged emotion differentiation	**-0.014 [-0.021, -0.007]**
Lagged emotion intensity	-0.016 [-0.040, 0.009]
Emotion regulation intensity	0.294 [-0.296, 0.884]
Time trend	**-0.003 [-0.004, -0.002]**
Lagged emotion differentiation, moderated by within-person emotion intensity	**0.002 [0.000, 0.003]**

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* *[95% CI]*
Between-person (time-invariant)	
Intercept	**3.902 [2.823, 4.982]**
Emotion differentiation	0.062 [-0.078, 0.202]
Emotion intensity	-0.023 [-0.129, 0.082]
Emotion regulation intensity	**-0.552 [-0.629, -0.476]**
Age	-0.005 [-0.061, 0.051]
Gender (female = 1, male = 0)	**0.411 [0.187, 0.636]**
Outcome: Strategy switching (Model 1B)	N = 752, n = 25867
Within-person (time-varying)	
Endorsement change	**-0.435 [-0.576, -0.293]**
Lagged emotion differentiation	**-0.007 [-0.012, -0.002]**
Lagged emotion intensity	-0.009 [-0.023, 0.005]
Emotion regulation intensity	**-0.102 [-0.149, -0.056]**
Time trend	**-0.002 [-0.002, -0.001]**
Lagged emotion differentiation, moderated by within-person emotion intensity	0.001 [0.000, 0.002]
Between-person (time-invariant)	
Intercept	**0.867 [0.242, 1.492]**
Emotion differentiation	**0.147 [0.077, 0.218]**
Emotion intensity	0.029 [-0.025, 0.082]
Emotion regulation intensity	0.009 [-0.030, 0.048]
Age	**0.038 [0.009, 0.067]**
Gender (female = 1, male = 0)	**0.143 [0.032, 0.255]**
Outcome: Endorsement change (Model 1C)	N = 752, n = 25867
Within-person (time-varying)	
Strategy switching	0.295 [-1.136, 1.726]
Lagged emotion differentiation	**-0.011 [-0.016, -0.006]**
Lagged emotion intensity	-0.016 [-0.033, 0.002]
Emotion regulation intensity	0.049 [-0.232, 0.330]
Time trend	**-0.002 [-0.003, -0.002]**
Lagged emotion differentiation, moderated by within-person emotion intensity	**0.001 [0.000, 0.002]**
Between-person (time-invariant)	
Intercept	**2.435 [1.546, 3.323]**
Emotion differentiation	**-0.120 [-0.223, -0.016]**
Emotion intensity	-0.074 [-0.152, 0.003]
Emotion regulation intensity	**-0.653 [-0.709, -0.596]**

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* [95% CI]
Age	-0.008 [-0.056, 0.040]
Gender (female = 1, male = 0)	**0.190 [0.026, 0.355]**
Within-person mediation (Model 1M)	N = 756, n = 52003
Within-person (time-varying)	
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.026 [-0.033, -0.018]**
Lagged emotion intensity → emotion regulation variability	-0.025 [-0.085, 0.034]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.085 [0.049, 0.120]**
Emotion regulation intensity → emotion intensity	**0.220 [0.142, 0.298]**
Lagged emotion intensity → emotion intensity	**0.261 [0.203, 0.318]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.009 [0.004, 0.014]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by within-person emotion intensity	**0.004 [0.003, 0.006]**
Emotion regulation variability → emotion intensity (b-path), moderated by within-person emotion regulation intensity	**0.023 [0.011, 0.035]**
Within-person mediation (Model 1M) with person-level emotion differentiation as a moderator to a-path and b-path	N = 756, n = 52003
Within-person (time-varying)	
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.025 [-0.032, -0.019]**
Lagged emotion intensity → emotion regulation variability	-0.026 [-0.085, 0.033]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.084 [0.052, 0.117]**
Emotion regulation intensity → emotion intensity	**0.222 [0.147, 0.297]**
Lagged emotion intensity → emotion intensity	**0.262 [0.207, 0.317]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.009 [0.004, 0.014]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by within-person emotion intensity	**0.004 [0.002, 0.005]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by between-person emotion differentiation	-0.003 [-0.007, 0.001]
Emotion regulation variability → emotion intensity (b-path), moderated by within-person emotion regulation intensity	**0.023 [0.012, 0.035]**
Emotion regulation variability → emotion intensity (b-path), moderated by between-person emotion differentiation	-0.016 [-0.039, 0.008]
Outcome: Emotion differentiation (Model 2A)	N = 751, n = 25830

Table S7

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability and Emotion Intensity, Examing the Potential Influence of Zero Negative Emotion (Regulation) Intensity (*continued*)

	Negative Emotions *b* *[95% CI]*
Within-person (time-varying)	
Emotion regulation variability	**-0.524 [-0.829, -0.219]**
Lagged emotion differentiation	-0.012 [-0.026, 0.003]
Emotion intensity	**-3.788 [-4.792, -2.784]**
Emotion regulation intensity	**0.096 [0.007, 0.186]**
Time trend	**-0.005 [-0.008, -0.003]**
Emotion regulation variability, moderated by within-person emotion regulation intensity	**-0.269 [-0.400, -0.138]**
Between-person (time-invariant)	
Intercept	**-1.118 [-1.819, -0.417]**
Emotion regulation variability	**-0.056 [-0.094, -0.019]**
Emotion intensity	**-0.191 [-0.252, -0.131]**
Emotion regulation intensity	**-0.078 [-0.124, -0.033]**
Age	**-0.050 [-0.088, -0.013]**
Gender (female = 1, male = 0)	0.040 [-0.085, 0.166]
Outcome: Emotion differentiation (Model 2B)	N = 751, n = 25830
Within-person (time-varying)	
Strategy switching	**-0.473 [-0.820, -0.127]**
Endorsement change	**-0.636 [-0.971, -0.302]**
Lagged emotion differentiation	-0.009 [-0.023, 0.006]
Emotion intensity	**-3.687 [-4.772, -2.603]**
Emotion regulation intensity	0.078 [-0.022, 0.178]
Time trend	**-0.006 [-0.008, -0.004]**
Endorsement change, moderated by within-person emotion regulation intensity	**-0.300 [-0.434, -0.165]**
Strategy switching, moderated by within-person emotion regulation intensity	**-0.332 [-0.483, -0.182]**
Between-person (time-invariant)	
Intercept	**-1.173 [-1.833, -0.513]**
Strategy switching	-0.030 [-0.096, 0.036]
Endorsement change	**-0.079 [-0.133, -0.025]**
Emotion intensity	**-0.184 [-0.244, -0.124]**
Emotion regulation intensity	**-0.087 [-0.135, -0.039]**
Age	**-0.049 [-0.084, -0.013]**
Gender (female = 1, male = 0)	0.048 [-0.076, 0.172]

Note. Significant effects are displayed in bold. n: number of ESM assessments; N: number of adolescents; b: unstandardized effect; CI: confidence interval. In Model 1M, n is doubled because of how data have undergone the stacking preparation step.

SUPPLEMENTAL MATERIALS 8: POTENTIAL INFLUENCE OF AGE: DATASET-SPECIFIC EFFECTS AND SENSITIVITY ANALYSES

In this section, we first present how within-person effects in our preregistered analyses vary across datasets (Table S8.1). Following this, we explore whether within-dataset age differences moderated the within-person effects of interest through sensitivity analyses.

Dataset-specific effects

Table S8.1 reveals that within-person results appeared stronger in datasets sampling late adolescents. This pattern suggests indicative evidence of age moderation in the within-person effects we studied. Indicative, because we cannot tease apart the influence of age differences from other study design features. In other words, the differences in strength of within-person results could have possibly been caused by study design features instead of age differences.

Table S8.1

Dataset-specific effects, given by sum of dataset-level random effects and fixed effects

Model	Index or path	Outside-in (Ghent)	G(F)ood together (Radboud)	3-wave longitudinal study (Leuven)	Emotions in daily life 2011 (Leuven)	Emotions in daily life (Tilburg)
	Age mean	13.486	16.434	18.322	19.053	20.879
	Age standard deviation	0.578	0.684	0.957	1.275	1.701
Model 1A (Negative emotion; Outcome: emotion regulation variability)	Lagged emotion differentiation	-0.008	-0.009	-0.013	-0.012	-0.005
Model 1B (Negative emotion; Outcome: strategy switching)	Lagged emotion differentiation	-0.003	-0.004	-0.005	-0.006	-0.002
Model 1C (Negative emotion; Outcome: endorsement change)	Lagged emotion differentiation	-0.003	-0.01	-0.01	-0.01	-0.007
Model 2A (Outcome: Negative emotion differentiation)	Emotion regulation variability	-0.193	-0.487	-0.605	-0.681	-0.605
Model 2B (Outcome: Negative emotion differentiation)	Endorsement change	-0.245	-0.473	-0.647	-0.752	-0.631
Model 2B (Outcome: Negative emotion differentiation)	Strategy switching	0.036	-0.38	-0.571	-0.678	-0.565
Model 1A (Positive emotion; Outcome: emotion regulation variability)	Lagged emotion differentiation	-0.004	-0.011	-0.012	-0.012	-0.008
Model 1B (Positive emotion; Outcome: strategy switching)	Lagged emotion differentiation	-0.002	-0.003	-0.005	-0.006	-0.002
Model 1C (Positive emotion; Outcome: endorsement change)	Lagged emotion differentiation	-0.002	-0.009	-0.01	-0.008	-0.006
Model 2A (Outcome: Positive emotion differentiation)	Emotion regulation variability	-0.084	-0.107	-0.341	-0.179	-0.671
Model 2B (Outcome: Positive emotion differentiation)	Endorsement change	-0.095	-0.117	-0.319	-0.161	-0.622

Table S8.1

Dataset-specific effects, given by sum of dataset-level random effects and fixed effects (*continued*)

Model	Index or path	Outside-in (Ghent)	G(F)ood together (Radboud)	3-wave longitudinal study (Leuven)	Emotions in daily life 2011 (Leuven)	Emotions in daily life (Tilburg)
Model 2B (Outcome: Positive emotion differentiation)	Strategy switching	-0.055	-0.118	-0.368	-0.292	-0.814
Model 1M (Negative emotion)	Lagged emotion differentiation → emotion regulation variability (a-path)	-0.009	-0.011	-0.016	-0.016	-0.012
Model 1M (Negative emotion)	Emotion regulation variability → emotion intensity (b-path)	0.092	0.1	0.05	0.03	0.092
Model 1M (Negative emotion)	Lagged emotion differentiation → emotion intensity (c′-path)	0.008	0.004	0.01	0.014	0.005
Model 1M (Positive emotion)	Lagged emotion differentiation → emotion regulation variability (a-path)	-0.013	-0.015	-0.016	-0.015	-0.015
Model 1M (Positive emotion)	Emotion regulation variability → emotion intensity (b-path)	-0.117	-0.055	-0.003	-0.029	-0.026
Model 1M (Positive emotion)	Lagged emotion differentiation → emotion intensity (c′-path)	-0.017	-0.018	-0.019	-0.019	-0.017

Sensitivity Analyses on Within-Dataset Age Differences

To further examine the role of age, we created a new variable, dataset-centered age, representing age differences within each dataset. Between-dataset age differences were already accounted for in the dataset-level random slopes. We calculated within-person moderators by multiplying the dataset-centered age with the within-person components of the independent variables (e.g., emotion differentiation in Model 1A). These moderators were added to all models (1A to 2B, positive and negative emotions), replacing the original age variable. To prevent the model from being overly complex for R packages' evaluation, random effects for the within-person moderators were not included.

Our analyses showed that the main effects of primary interest (e.g., emotion differentiation in Model 1A) remained consistent in direction and statistical significance across models. The only exception was the b-path (from emotion regulation variability to positive emotion intensity) in Model 1M (positive emotion), where the estimate maintained its original direction but its 95% confidence interval narrowly crossed zero into the positive range (0.000). These findings suggest that our results are generally robust against within-dataset age differences. Regardless of the dataset-level variations in and within-dataset age differences' on strength of within-person effects, we can still conclude there are fixed effects across the participants from the five datasets we studied on the within-person processes we hypothesized on.

Table S8.2

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability, and Emotion Intensity, with Within-Dataset Age Differences as a Moderator

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Outcome: Emotion regulation variability (Model 1A)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		
Lagged emotion differentiation	**-0.009 [-0.014, -0.005]**	**-0.009 [-0.014, -0.004]**
Lagged emotion differentiation, moderated by within-dataset age difference	-0.001 [-0.003, 0.002]	-0.002 [-0.005, 0.001]
Lagged emotion intensity	-0.018 [-0.044, 0.008]	-0.005 [-0.017, 0.007]
Emotion regulation intensity	0.294 [-0.285, 0.874]	0.280 [-0.275, 0.834]
Time trend	**-0.003 [-0.004, -0.003]**	**-0.003 [-0.004, -0.002]**
Between-person (time-invariant)		
Intercept	**3.817 [3.347, 4.287]**	**3.848 [3.386, 4.310]**
Emotion differentiation	0.069 [-0.071, 0.209]	-0.049 [-0.255, 0.158]
Emotion intensity	-0.022 [-0.128, 0.084]	**-0.107 [-0.181, -0.034]**
Emotion regulation intensity	**-0.553 [-0.630, -0.476]**	**-0.561 [-0.630, -0.492]**
Within-dataset age difference	0.010 [-0.086, 0.106]	0.009 [-0.087, 0.105]
Gender (female = 1, male = 0)	**0.410 [0.186, 0.634]**	**0.347 [0.120, 0.575]**
Outcome: Strategy switching (Model 1B)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		
Endorsement change	**-0.439 [-0.577, -0.301]**	**-0.440 [-0.572, -0.307]**
Lagged emotion differentiation	**-0.004 [-0.007, -0.002]**	**-0.004 [-0.007, -0.001]**
Lagged emotion differentiation, moderated by within-dataset age difference	**-0.002 [-0.003, 0.000]**	-0.002 [-0.004, 0.001]
Lagged emotion intensity	-0.010 [-0.025, 0.005]	-0.002 [-0.013, 0.009]
Emotion regulation intensity	**-0.102 [-0.152, -0.052]**	**-0.102 [-0.152, -0.052]**
Time trend	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.002, -0.001]**
Between-person (time-invariant)		
Intercept	**1.535 [1.110, 1.959]**	**1.544 [1.138, 1.950]**
Endorsement change	0.017 [-0.027, 0.061]	0.008 [-0.036, 0.052]
Emotion differentiation	**0.154 [0.084, 0.225]**	0.016 [-0.091, 0.122]
Emotion intensity	0.031 [-0.023, 0.085]	-0.036 [-0.073, 0.002]
Emotion regulation intensity	0.014 [-0.029, 0.058]	0.011 [-0.029, 0.052]
Within-dataset age difference	0.026 [-0.023, 0.074]	0.023 [-0.025, 0.072]
Gender (female = 1, male = 0)	**0.138 [0.025, 0.251]**	**0.124 [0.009, 0.239]**
Outcome: Endorsement change (Model 1C)	N = 752, n = 25867	N = 751, n = 25851
Within-person (time-varying)		

Table S8.2

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability, and Emotion Intensity, with Within-Dataset Age Differences as a Moderator (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Strategy switching	0.312 [-1.138, 1.762]	0.303 [-1.136, 1.741]
Lagged emotion differentiation	**-0.008 [-0.012, -0.004]**	**-0.007 [-0.012, -0.003]**
Lagged emotion differentiation, moderated by within-dataset age difference	0.001 [-0.001, 0.002]	-0.001 [-0.004, 0.001]
Lagged emotion intensity	-0.017 [-0.034, 0.000]	-0.004 [-0.012, 0.004]
Emotion regulation intensity	0.053 [-0.234, 0.340]	0.058 [-0.228, 0.344]
Time trend	**-0.002 [-0.003, -0.002]**	**-0.002 [-0.003, -0.001]**
Between-person (time-invariant)		
Intercept	**2.275 [1.996, 2.554]**	**2.278 [2.004, 2.551]**
Strategy switching	**-0.234 [-0.318, -0.150]**	**-0.238 [-0.322, -0.154]**
Emotion differentiation	-0.081 [-0.183, 0.021]	-0.145 [-0.293, 0.004]
Emotion intensity	-0.071 [-0.147, 0.005]	0.025 [-0.028, 0.078]
Emotion regulation intensity	**-0.677 [-0.733, -0.621]**	**-0.695 [-0.746, -0.644]**
Within-dataset age difference	0.007 [-0.061, 0.076]	0.005 [-0.063, 0.073]
Gender (female = 1, male = 0)	**0.215 [0.054, 0.376]**	**0.204 [0.041, 0.367]**
Within-person mediation (Model 1M)	N = 752, n = 51697	N = 751, n = 51685
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.013 [-0.018, -0.008]**	**-0.014 [-0.020, -0.008]**
Lagged emotion intensity → emotion regulation variability	-0.029 [-0.082, 0.024]	-0.005 [-0.026, 0.016]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.073 [0.039, 0.108]**	**-0.049 [-0.092, -0.006]**
Emotion regulation intensity → emotion intensity	**0.234 [0.166, 0.302]**	**-0.101 [-0.189, -0.013]**
Lagged emotion intensity → emotion intensity	**0.258 [0.202, 0.315]**	**0.300 [0.249, 0.350]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.008 [0.003, 0.013]**	**-0.016 [-0.026, -0.006]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.003, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by within-dataset age difference	-0.001 [-0.004, 0.002]	-0.004 [-0.009, 0.000]
Emotion regulation variability → emotion intensity (b-path), moderated by within-dataset age difference	-0.010 [-0.027, 0.007]	0.011 [-0.010, 0.033]
Mediation (sum of covariance and product of a- and b-path)	-0.000 [-0.001, 0.000]	-0.000 [-0.001, 0.001]

Table S8.2

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability, and Emotion Intensity, with Within-Dataset Age Differences as a Moderator (*continued*)

	Negative Emotions *b* [95% CI]	**Positive Emotions *b* [95% CI]**
Within-person mediation (Model 1M) with person-level emotion differentiation as a moderator to a-path and b-path	N = 752, n = 51697	N = 751, n = 51685
Within-person (time-varying)		
Lagged emotion differentiation → emotion regulation variability (a-path)	**-0.015 [-0.020, -0.010]**	**-0.016 [-0.022, -0.010]**
Lagged emotion intensity → emotion regulation variability	-0.030 [-0.084, 0.023]	-0.005 [-0.028, 0.018]
Time trend → emotion regulation variability	**-0.005 [-0.006, -0.004]**	**-0.005 [-0.005, -0.004]**
Emotion regulation variability → emotion intensity (b-path)	**0.074 [0.038, 0.111]**	**-0.048 [-0.094, -0.003]**
Emotion regulation intensity → emotion intensity	**0.236 [0.164, 0.307]**	**-0.101 [-0.200, -0.003]**
Lagged emotion intensity → emotion intensity	**0.258 [0.201, 0.315]**	**0.300 [0.250, 0.350]**
Lagged emotion differentiation → emotion intensity (c'-path)	**0.008 [0.003, 0.014]**	**-0.016 [-0.025, -0.007]**
Time trend → emotion intensity	**-0.002 [-0.002, -0.001]**	**-0.002 [-0.003, -0.001]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by between-person emotion differentiation	**-0.006 [-0.009, -0.002]**	**-0.011 [-0.021, 0.000]**
Lagged emotion differentiation → emotion regulation variability (a-path), moderated by within-dataset age difference	-0.001 [-0.004, 0.002]	**-0.005 [-0.009, 0.000]**
Emotion regulation variability → emotion intensity (b-path), moderated by between-person emotion differentiation	**-0.034 [-0.057, -0.011]**	**0.049 [0.000, 0.097]**
Emotion regulation variability → emotion intensity (b-path), moderated by within-dataset age difference	-0.011 [-0.028, 0.006]	0.013 [-0.009, 0.035]
Outcome: Emotion differentiation (Model 2A)	N = 751, n = 25830	N = 750, n = 25834
Within-person (time-varying)		
Emotion regulation variability	**-0.504 [-0.717, -0.290]**	**-0.282 [-0.517, -0.047]**
Emotion regulation variability, moderated by within-dataset age difference	-0.014 [-0.093, 0.064]	-0.028 [-0.074, 0.018]
Lagged emotion differentiation	**-0.018 [-0.031, -0.006]**	0.030 [0.000, 0.061]
Emotion intensity	**-3.885 [-5.056, -2.714]**	**0.528 [0.200, 0.855]**
Emotion regulation intensity	-0.028 [-0.110, 0.054]	**-0.153 [-0.253, -0.053]**
Time trend	**-0.006 [-0.008, -0.004]**	**0.004 [0.003, 0.006]**
Between-person (time-invariant)		

Table S8.2

Fixed Effect Estimates of Within-Person Temporal Associations and Between-Person Differences in Between Emotion Differentiation, Emotion Regulation Variability, and Emotion Intensity, with Within-Dataset Age Differences as a Moderator (*continued*)

	Negative Emotions *b* *[95% CI]*	**Positive Emotions *b* *[95% CI]***
Intercept	**-2.034 [-2.265, -1.804]**	**-1.754 [-2.269, -1.238]**
Emotion regulation variability	-0.035 [-0.071, 0.001]	-0.012 [-0.039, 0.015]
Emotion intensity	**-0.237 [-0.296, -0.179]**	**0.034 [0.004, 0.064]**
Emotion regulation intensity	-0.043 [-0.087, 0.001]	-0.015 [-0.044, 0.015]
Within-dataset age difference	-0.037 [-0.088, 0.014]	**-0.078 [-0.117, -0.040]**
Gender (female = 1, male = 0)	0.044 [-0.076, 0.165]	**-0.150 [-0.240, -0.059]**
Outcome: Emotion differentiation (Model 2B)	N = 751, n = 25830	N = 750, n = 25834
Within-person (time-varying)		
Strategy switching	**-0.418 [-0.717, -0.118]**	**-0.334 [-0.615, -0.054]**
Endorsement change	**-0.545 [-0.768, -0.321]**	**-0.267 [-0.470, -0.064]**
Endorsement change, moderated by within-dataset age difference	0.009 [-0.075, 0.092]	-0.058 [-0.117, 0.001]
Strategy switching, moderated by within-dataset age difference	-0.024 [-0.106, 0.058]	-0.002 [-0.050, 0.046]
Lagged emotion differentiation	**-0.019 [-0.031, -0.007]**	0.030 [-0.002, 0.061]
Emotion intensity	**-3.927 [-4.989, -2.865]**	**0.520 [0.196, 0.845]**
Emotion regulation intensity	-0.036 [-0.120, 0.048]	**-0.158 [-0.249, -0.067]**
Time trend	**-0.006 [-0.008, -0.004]**	**0.005 [0.003, 0.006]**
Between-person (time-invariant)		
Intercept	**-2.041 [-2.251, -1.832]**	**-1.754 [-2.246, -1.262]**
Strategy switching	0.055 [-0.008, 0.119]	-0.004 [-0.052, 0.044]
Endorsement change	**-0.092 [-0.141, -0.042]**	-0.018 [-0.054, 0.019]
Emotion intensity	**-0.238 [-0.295, -0.180]**	**0.034 [0.004, 0.064]**
Emotion regulation intensity	**-0.068 [-0.114, -0.022]**	-0.016 [-0.048, 0.016]
Within-dataset age difference	-0.034 [-0.085, 0.017]	**-0.077 [-0.116, -0.038]**
Gender (female = 1, male = 0)	0.034 [-0.086, 0.154]	**-0.151 [-0.241, -0.061]**

Note. Significant effects are displayed in bold. n: number of ESM assessments; N: number of adolescents; b: unstandardized effect; CI: confidence interval. In Model 1M, n is doubled because of how data have undergone the stacking preparation step.

Appendix C

Supplemental Materials for Chapter 4 (Negative Emotion Transitions Are Temporally Close to Reductions in Overall Negative Emotion Intensity in Daily Life)

SUPPLEMENTAL MATERIAL 1: DETAILS ON PARTICIPANTS AND PROCEDURES OF THE THREE DATASETS

Please note that while the ESM measure descriptions are presented in English in this document, the actual questionnaires were administered in German for Dataset 1 and in Dutch for Datasets 2 and 3.

In describing the ESM items we used, we listed their omega reliability of forming a negative emotion intensity index (i.e., a one-factor model from the perspective from confirmatory factor analysis) within and between participants. Additionally, we cited earlier studies that have used the same ESM items. These two steps were recommended as practices that allowed researchers to better assess the validity of ESM measures given the current state of development in ESM measures validation (Vogelsmeier et al., 2023).

Dataset 1

Participants

Participants took part in the study in 2015. They were university students from Humboldt-Universität zu Berlin, and the study received ethical approval from the university's ethics committee. Recruitment was conducted via posters, online advertisements, and university mailing lists. All participants completed the German version of the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977; German translation by Hautzinger & Bailer, 1993). No participants were excluded in the original study. As reaction time data were unavailable, no exclusions were made for potentially careless responding. The final sample included 70 participants, with a mean age of 25.55 years (SD = 2.74), and an equal gender distribution (50% women).

Procedure

Participants completed two laboratory sessions, providing informed consent at the outset. The experience sampling method (ESM) phase took place between these two sessions. During the first session, participants completed the CES-D and additional questionnaires unrelated to the present study. They were then given standardized smartphones (Huawei Ascend G330) preloaded with an ESM assessment app previously used in other research (Rauers et al., 2013; Riediger et al., 2009). The ESM phase began the day after the first session and spanned 9 days. Each day, participants received 6 semi-random prompts within a 12-hour time window of their choosing. These prompts were spaced with at least 45 minutes between them and distributed randomly within 2-hour blocks. If participants missed more than one prompt per day, they could extend the ESM period by up to three days.

The original study did not specify whether prompts had a response time limit or if reminders were used. Nevertheless, compliance was high: based on the intended 54 prompts (6 per day over 9 days), participants completed 101% on average (SD = 6%, range: 89–120%, or 48–65 prompts). Participants received a fixed payment for lab sessions and an additional €10 based on the number of completed ESM entries. On average, total compensation was 65 Euros.

ESM emotion items

At each momentary assessment, participants rated three negative emotions: nervous, downhearted, and distressed. These items have been employed in various ESM studies (Forkmann et al., 2018; Houtveen et al., 2022; Riediger et al., 2009; Simor et al., 2015; Zetsche, Bürkner, et al., 2024; Zetsche et al., 2019; Zetsche, Neumann, et al., 2024). These ratings were provided on a 7-point scale, ranging from 0, indicating "does not apply at all," to 6, indicating "applies strongly." The stem for these items was: "How have you primarily felt since the last measurement / since waking up (for the first beep of the day)? Please rate how well the following emotion adjectives describe your feelings during this time period." The omega reliability of the negative emotions scale was satisfactory within (.68) and between young adults (.93).

Dataset 2

Participants

Participants were sourced from a group of 439 undergraduates at the University of Leuven, Belgium, and the study received ethical approval from the university ethics committee (protocol number: ML7321). All participants completed a Dutch version of the CES-D (Radloff, 1977) and were selected to ensure a wide range of depression scores. 100 participants took part in the study in 2011, but three were excluded due to device malfunctions, one withdrew from the study, and one was excluded due to poor compliance (more than 40% missing data, see Brans et al., 2013). After these exclusions, the sample represented in the public dataset comprised 95 participants, with an average age of 19.05 years (SD = 1.27), of whom 63% were women. The majority of participants were of Belgian nationality (97%). Before our analysis, one participant was further excluded because there was no variance in CES-D items, where reverse items were present, indicating potentially problematic responses. This made the final sample comprise of 94 participants.

Procedure

Participants attended an introductory session in the laboratory where they provided informed consent, completed unrelated questionnaires unrelated to the current research, and received standardized Tungsten E2 PalmOne devices (Mankato, MN) programmed for ESM item assessments. The ESM study commenced the next day, lasting 7 days, with 10 semi-random beeps each day during a 12-hour window. Participants were told each measurement would take about 1 minute. They were required to respond to the questionnaire within 2 minutes of notification. Each question had a 90-second response window before timing out. No reminders were issued for missed momentary assessments. On average, participants completed 91.5% of the beeps (SD = 6.2%, range: 67–100% of all beeps). Participants received 70 Euros for completing the study.

ESM emotion items

During each momentary assessment, participants rated four negative emotions, angry, sad, anxious, and depressed, on a 100-point slider scale ranging from 1, meaning "not at all", to 100, meaning "very much". The prompt for these items was "How [emotion] do you feel at the moment?". These items have been employed in various ESM studies (Achterhof et al., 2022; J. M. Bakker et al., 2017; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Brans et al., 2013; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006). With 10 assessments daily over 7 days, the maximum potential number of measurements for both negative and positive emotions was 70. The reliability of the negative emotions ratings was found to be satisfactory within (.76) and between young adults (.94).

Dataset 3

Participants

The participants were undergraduates from the University of Leuven, Belgium, and the ethics committee of the University of Leuven approved this three-wave study (protocol number: ML8514). However, only the first-wave data collected in 2012 were analyzed in this instance. A total of 686 first-year undergraduates completed the Dutch version CES-D (Radloff, 1977; Wu et al., 2016) as a prescreening measure. From this, 180 participants were selected using a stratified sampling method ensuring equal representation from the four CES-D distribution quartiles. Additionally, 22 participants joined without completing the CES-D, bringing the total number to 202 participants. In this sample represented by the dataset extracted from EMOTE, the average age was 18.32 years (SD = 0.96), with 55% women. The majority, 93%, were of Belgian nationality. Before our analysis, one participant was further excluded because there was no variance in their CES-D items, where reverse items were present, indicating potentially problematic responses. This made the final sample 201 participants.

Procedure

In an introductory laboratory session, participants completed questionnaires unrelated to the study. They received standardized Motorola Defy Plus devices with custom-built ESM software and were trained in using these phones for filling out ESM questionnaires. Participants practiced with the ESM questionnaire and had the opportunity to ask questions to an experimenter before departing the lab. The ESM study spanned 7 consecutive days, with 10 semi-random beeps each day over a 12-hour time frame. Participants were told that each measurement would take 1-2 minutes. Once participants opened the questionnaire, they had 90 seconds to answer each question before it timed out, and there were no reminders if they missed a momentary assessment. Participants responded to 87.27% of the beeps (SD = 9.05%, range: 67–100%). They received a reimbursement of 60 Euros for this wave, with eligibility for an additional 60 Euros for completing all three study waves.

ESM emotion items

During each momentary assessment, participants rated six negative emotions—lonely, angry, anxious, sad, depressed, and stressed—using a slider scale ranging from 0 ("not at all") to 100 ("very much"). The prompt for these ratings was "How [emotion] do you feel at the moment?". These measures have previously been applied in various ESM studies (Achterhof et al., 2022; J. M. Bakker et al., 2017; Barge-Schaapveld et al., 1999; Bastiaansen et al., 2018; Bennik, 2015; Brans et al., 2013; Bülow et al., 2022; Delespaul & DeVries, 1987; Fried et al., 2022; Hasmi et al., 2017; Jacobs et al., 2007; Kiekens et al., 2023; Myin-Germeys et al., 2000; Rauschenberg et al., 2017; Schneiders et al., 2006). Spanning 10 daily assessments over seven days, the maximum possible number of measurements was 70. The omega reliability for the negative emotion ratings was found to be satisfactory within (.73) and between young adults (.93).

SUPPLEMENTARY MATERIAL 2: CALCULATING THE REPLACEMENT AND NESTEDNESS SUBCOMPONENTS OF BRAY-CURTIS DISSIMILARITY

This Supplemental Material presents the formula for calculating Bray-Curtis dissimilarity, including its full index and its two subcomponents: replacement and nestedness (Baselga, 2013b). Intermediate steps are commonly used in calculating the full index and its subcomponents (Table S2.1).

Table S2.1

Formulae of the Bray-Curtis Dissimilarity Index and its Subcomponents

	Formula	
Intermediate Steps		
A (Shared ratings across $x_{(t)}$ and $x_{(t-1)}$)	$\sum_{e \in E} min\left(x_{e(t)}, x_{e(t-1)}\right)$	
B (Exclusive ratings of $x_{(t)}$)	$\sum_{e \in E}^{N} x_{e(t)} - A$	
C (Exclusive ratings of $x_{(t-1)}$)	$\sum_{e \in E} x_{e(t-1)} - A$	
Bray-Curtis Dissimilarity and its subcomponents		
Full index	$\sum_{e \in E} \frac{\left\lvert x_{e(t)} - x_{e(t-1)} \right\rvert}{x_{e(t)} + x_{e(t-1)}} \equiv$	$\frac{B+C}{2A+B+C}$
Replacement	$1 - \frac{\sum_{e \in E} min\left(x_{e(t)}, x_{e(t-1)}\right)}{min\left(\sum_{e \in E} x_{e(t)},\ \sum_{e \in E} x_{e(t-1)}\right)} \equiv$	$\frac{min(B,C)}{A+min(B,C)}$
Nestedness	$\frac{\lvert B-C \rvert}{2A+B+C} \times \frac{A}{A+min(B,C)}$	$\equiv$ Full index - replacement

Note. *x* is a set of all reported intensity of emotions across all measurement occasions within a person. $x_{e(t)}$ refers to a specific intensity of an emotion (out of a set of *E* emotions) of the t^{th} moment, and $x_{e(t-1)}$ the $(t\text{-}1)^{th}$ moment, i.e., the measurement previous to *t*. A, B, and C are intermediate calculation steps compute Bray-Curtis dissimilarity (MacGregor-Fors et al., 2022).

To illustrate their application in experience sampling method (ESM) data, we provide example calculations of the intermediate steps (Table S2.2) and the index (plus its subcomponents; Table S2.3) using the example data that correspond to Figure S2.1 and Figure S2.2 (which are copies of Figure 4.1 and Figure 4.2 of the main text).

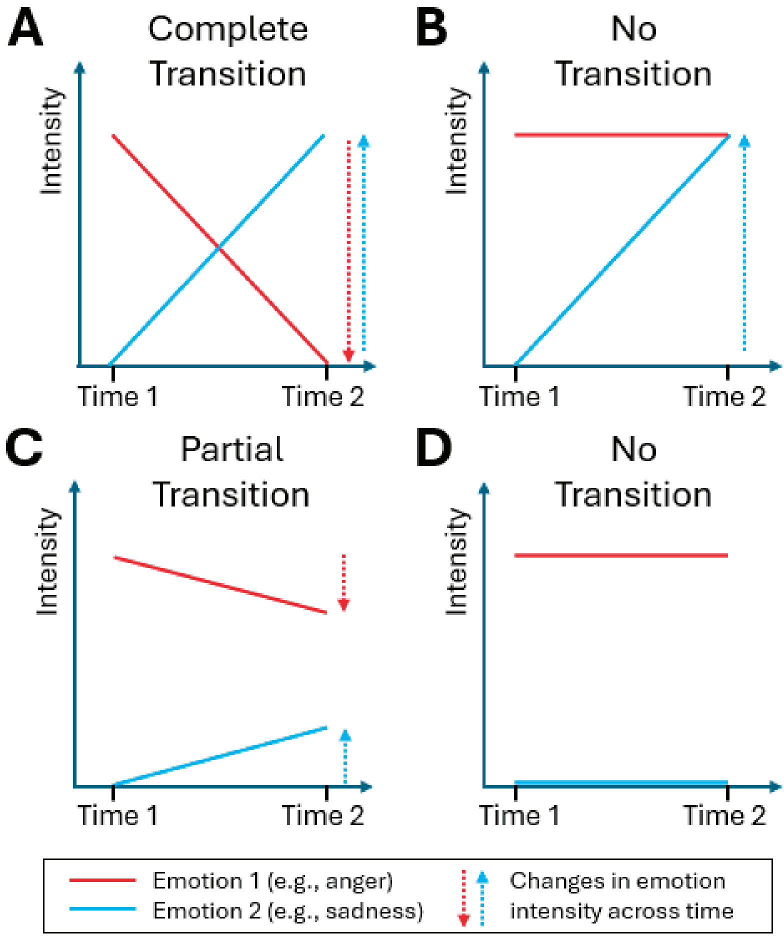


Figure S2.1

Example patterns of complete, no, and partial negative emotion transitions.

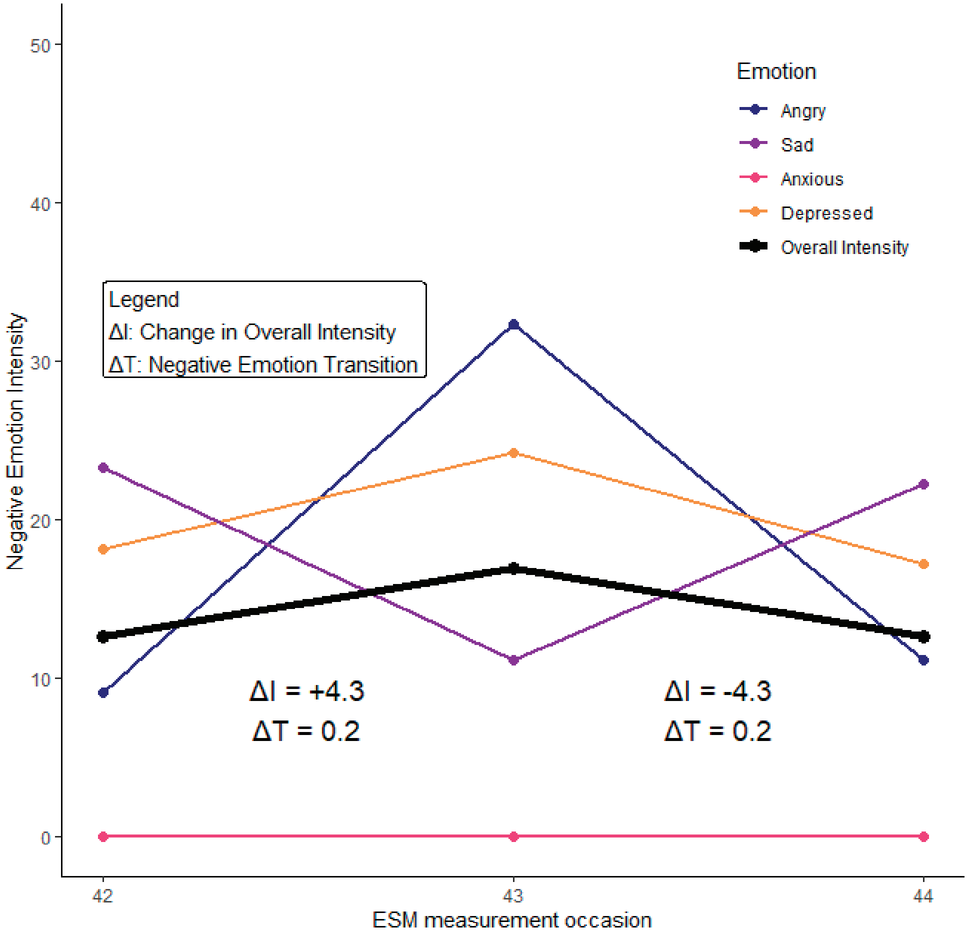


Figure S2.2

Excerpts of three ESM measurements from a participant from Dataset 2.

Table S2.2

Calculation of Intermediate Steps

	Anger Intensity		**Sadness Intensity**		**Anxiety Intensity**		**Intermediate Steps (A, B, C): Formulae and calculations**		
	T1	T2	T1	T2	T1	T2	A = $\sum_{e \in E} min\left(x_{e(T1)}, x_{e(T2)}\right)$	B = $\sum_{e \in E}^{N} x_{e(T1)} - A$	C = $\sum_{e \in E} x_{e(T2)} - A$
Figure S2.1									
Panel A	6	0	0	6	-	-	0 + 0 = 0	6 + 0 – 0 = 6	0 + 6 – 0 = 6
Panel B	6	6	0	6	-	-	0 + 6 = 6	6 + 0 – 6 = 0	6 + 6 – 6 = 6
Panel C	6	4	0	2	-	-	0 + 2 = 2	6 + 0 – 2 = 4	4 + 2 – 2 = 4
Panel D	6	6	0	0	-	-	6 + 0 = 6	6 + 0 – 6 = 0	6 + 0 – 6 = 0
Figure S2.2									
t: 42 to 43 (T1 to T2)	9	32	23	11	18	24	9 + 11 + 18 = 38	(9 + 23 + 18) - 38 = 12	(32 + 11 + 24) – 38 = 29
t. 43 to 44 (T1 to T2)	32	11	11	22	24	17	11 + 11 + 17 = 39	(32 + 11 + 24) – 39 = 28	(11 + 22 + 17) – 39 = 11

Table S2.3

Calculation of the Bray-Curtis Dissimilarity Full Index and its Subcomponents with Results of Intermediate Steps obtained in Table S2.2

	Anger Intensity		***Sadness Intensity***		***Anxiety Intensity***		***Using Intermediate Steps (A, B, C) for Calculating Bray-Curtis Dissimilarity and its Subcomponents***		
	T1	T2	T1	T2	T1	T2	Full index $= \frac{B+C}{2A+B+C}$	Replacement subcomponent $= \frac{min(B,C)}{A+min(B,C)}$	Nestedness subcomponent = Full index – replacement sub-component
Figure S2.1									
Panel A	6	0	0	6	-	-	(6 + 6) / (0 + 6 + 6) = 1	min(6,6)/(0+min(6,6)) = 1	1 – 1 = 0
Panel B	6	6	0	6	-	-	(0 + 6)/(6*2+0+6) = 0.33	min(0,6)/(6+min(0,6)) = 0	0.33 – 0 = 0.33
Panel C	6	4	0	2	-	-	(4+4)/(2*2+4+4) = 0.67	min(4,4)/(2+min(4,4)) = 0.67	0.67-0.67 = 0
Panel D	6	6	0	0	-	-	(0+0)/(6*2+0+0) = 0	min(0,0)/(6+min(0,0)) = 0	0 – 0 = 0
Figure S2.2									
t: 42 to 43 (T1 to T2)	9	32	23	11	18	24	(12+29)/(38*2+12+29) = 0.35	min(12,29)/(38+min(12,29) = 0.24	0.35 – 0.24 = 0.11
t. 43 to 44 (T1 to T2)	32	11	11	22	24	17	(28+11)/(39*2+28+11) = 0.33	min(28,11)/(39+min(28,11)) = 0.22	0.33 – 0.22 = 0.11

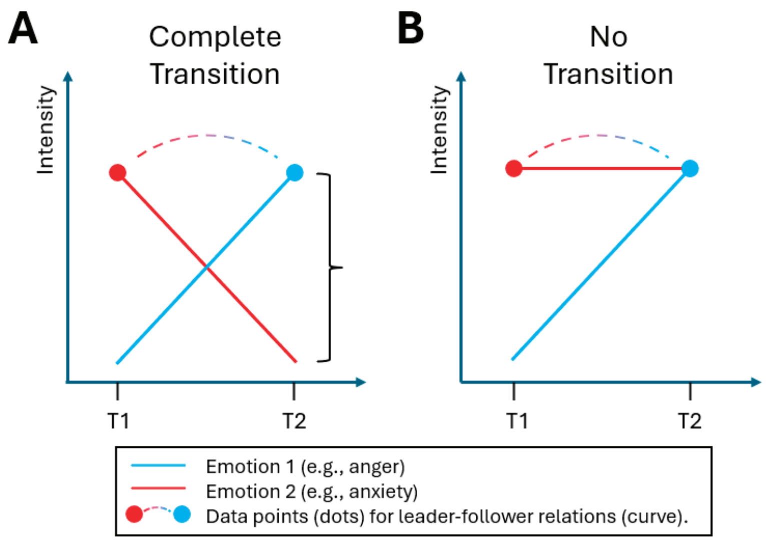
SUPPLEMENTAL MATERIAL 3: WHY THE REPLACEMENT SUBCOMPONENT IS ADVANTAGEOUS TO OTHER APPROACHES IN CAPTURING EMOTION TRANSITIONS

Versus the "Leader-Follower" Approach

The "leader-follower" method – also called the cross-lagged effect – is a commonly used approach that examines how the intensity of one "leader" emotion predicts the intensity of another "follower" emotion at a later time point. For instance, anger at one moment might predict sadness at the next (blue dots, red dots, and their connecting curves in Figure S3). This approach depicts how intensity of one emotion may activate intensity of other emotions in daily life. For example, individuals, after experiencing a negative emotion, are more likely to experience another negative emotion than another positive emotion (Thornton & Tamir, 2017); This negative-to-negative emotion temporal predictive likelihood is higher in depressed than in healthy individuals (Pe et al., 2015). However, leader-follower relations disregard the prior intensity of the "follower" emotion and the subsequent intensity of the "leader" emotion, resulting in insufficient detection of emotion transition. In Figures S3A and S3B, where the subsequent intensity of the "leader" emotion varies, different degrees of emotion transition and net changes in intensity can result in the same leader-follower relation. Therefore, this approach cannot sufficiently capture the phenomena of emotion transitions and is not suitable for the current study.

Figure S3

Different patterns of intensity changes of two emotions over two time points (T1 and T2) that result in complete (Panel A) and no transition (Panel B). The leader-follower relations (curves)are be insensitive to underlying emotion transitions.



Versus Other Approaches Commonly used in Emotion Dynamics

Lo et al. (2024)'s simulation study investigated which index has better performance in capturing switching between emotion regulation (ER) strategies across time, which is analogous to transitions between emotions across time. In summary, conventional *SD*-based methods are less sensitive to the compensatory patterns of change and may not detect ER strategy switching (or emotion transition when applied to our study), especially when it occurs without changes in overall strategy use intensity (overall emotion intensity). Simulation studies confirmed that Bray-Curtis dissimilarity and its replacement subcomponent were significantly more sensitive to experimentally introduced strategy switching (emotion transition in our study) than SD-based measures.

Versus Other Indices Commonly used in Ecology

In ecology, other than Bray-Curtis dissimilarity, there are other dissimilarity indices that can capture compensatory replacements. MacGregor-Fors et al. (2022)'s study compared 12 ecological indices. Their analysis showed that the replacement subcomponent of Bray-Curtis dissimilarity stands out among the assessed indices for detecting species turnover due to its predictable behavior. It consistently shows a linear decrease with diminishing species composition overlap. A significant advantage is its insensitivity to differences in species richness (an ecological term describing the total number of organisms across all species observed), which in our study means it returns consistent values regardless of overall intensity change. This linearity and independence from intensity change make the replacement subcomponent easily interpretable. In contrast, many other indices exhibit non-linear responses or are heavily influenced by differences in species richness (in our study context: overall emotion intensity), potentially leading to misinterpretations.

SUPPLEMENTAL MATERIAL 4: DESCRIPTIVE STATISTICS AND CORRELATIONS BETWEEN EMOTION ITEMS

Table S4

Descriptive Statistics and Correlations of the Negative Emotion Items (Range: 0-100) in the Three Datasets

									Within-person (lower triangle) correlations and between-person (upper triangle) correlations [95% confidence interval]					
Dataset	Negative Emotion	nobs	mean	wSD	bSD	ICC	min	max	i	ii	iii	iv	v	vi
1	i. Nervous	3824	27.36	19.94	16.02	0.36	2.86	79.05		.73 [.60,.83]	.75 [.63,.84]			
	ii. Downhearted	3826	19.45	17.30	15.60	0.40	1.43	72.62	.22 [.19,.25]		.90 [.84,.93]			
	iii. Distressed	3825	23.02	18.23	16.89	0.42	2.14	76.19	.31 [.28,.34]	.60 [.58,.62]				
2	i. Angry	5678	13.52	13.67	9.59	0.28	0.48	64.41		.67 [.54,.77]	.64 [.50,.74]	.64 [.50,.74]		
	ii. Sad	5676	17.26	14.82	12.81	0.37	1.00	64.80	.39 [.37,.41]		.78 [.68,.85]	.94 [.91,.96]		
	iii. Anxious	5677	12.63	11.46	10.74	0.39	0.64	54.21	.31 [.29,.33]	.39 [.37,.41]		.77 [.68,.84]		
	iv. Depressed	5677	16.27	12.70	14.93	0.50	1.55	56.86	.39 [.37,.41]	.64 [.63,.66]	.38 [.36,.41]			
3	i. Angry	12289	11.93	12.87	8.22	0.24	0.94	64.4		.84 [.80,.88]	.83 [.79,.87]	.79 [.73,.84]	.57 [.47,.66]	.60 [.50,.68]
	ii. Sad	12289	13.16	13.02	9.41	0.29	0.89	62.98	.42 [.41,.44]		.82 [.78,.86]	.89 [.86,.92]	.61 [.51,.69]	.72 [.65,.78]
	iii. Anxious	12289	10.34	9.92	8.11	0.33	0.85	53.06	.30 [.29,.32]	.39 [.37,.40]		.85 [.81,.89]	.62 [.53,.70]	.70 [.62,.76]

Table S4

Descriptive Statistics and Correlations of the Negative Emotion Items (Range: 0-100) in the Three Datasets (*continued*)

								Within-person (lower triangle) correlations and between-person (upper triangle) correlations [95% confidence interval]					
iv. Depressed	12289	12.68	12.01	9.83	0.33	0.94	57.21	.41 [.40,.43]	.59 [.57,.60]	.38 [.37,.40]		.62 [.53,.70]	.75 [.68,.80]
v. Stressed	12289	23.31	19.69	11.66	0.24	1.32	78.71	.31 [.29,.32]	.28 [.26,.29]	.31 [.30,.33]	.31 [.29,.33]		.53 [.42,.62]
vi. Lonely	12289	17.88	16.58	13.29	0.34	1.12	69.43	.21 [.20,.23]	.37 [.36,.39]	.22 [.21,.24]	.35 [.34,.37]	.18 [.17,.20]	

Note. nobs: number ESM observations. bSD: between-person SD of within-person mean; wSD: mean within-person SD across all young adults; ICC: intraclass correlation coefficient.

SUPPLEMENTAL MATERIAL 5: COMPLETE MULTILEVEL RESULTS FOR MODELS 1 AND 2 WITH BOOTSTRAPPED CONFIDENCE INTERVALS FOR KEY FIXED EFFECTS

In comparing model fits, it is desirable to have low Akaike Information Criterion (AIC), low Bayesian Information Criterion (BIC), high log-likelihood (i.e., close to 0), and low root mean squared error (RMSE). As seen from Table S5, Model 1 was preferred when judged by BIC, but Model 2 was preferred when judged by AIC, log-likelihood, and RMSE. BIC penalizes the complexity of a model. Hence, these selection criteria in general favour Model 2, although the improved model-data fit was not justified by the increased model complexity of Model 2 when judged by BIC. Given the theoretical importance of examining negative emotion transitions both as a main effect and as moderated by depressive symptoms, we present and interpret results from both models.

Table S5

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Momentary Negative Emotion Intensity

	Estimates [95% Confidence Interval (CI)]		
		Dataset	
Momentary Negative Emotion Intensity Regressed on	1 (N = 70, n = 2936)	2 (N = 94, n = 4651)	3 (N = 201, n = 10000)
Model 1			
Within-person (time-variant)			
Negative Emotion Transitions[#]	-3.05 [-6.03, -0.07]*	-3.89 [-6.31, -1.48]**	-3.41 [-5.02, -1.80]***
(Bootstrapped 95% CI)	*[-6.23, -0.93]*	*[-5.79, -2.03]*	*[-4.65, -2.27]*
Nestedness Subcomponent	-4.05 [-6.30, -1.80]***	-0.03 [-2.19, 2.13]	-2.32 [-3.82, -0.83]**
Lagged Negative Emotion Intensity	0.33 [0.27, 0.39]***	0.33 [0.28, 0.38]***	0.34 [0.30, 0.37]***
Time Trend	0.04 [0.01, 0.06]**	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	23.45 [20.74, 26.16]***	14.78 [12.87, 16.69]***	14.81 [13.76, 15.85]***
Negative Emotion Transitions	-16.08 [-53.92, 21.76]	-22.07 [-42.03, -2.11]*	-29.17 [-42.28, -16.06]***
Nestedness Subcomponent	-50.50 [-67.38, -33.62]***	-27.04 [-40.65, -13.44]***	-30.53 [-38.31, -22.75]***
Akaike Information Criterion	23,867.02	34,841.81	73,254.25
Bayesian Information Criterion	23,980.68	34,964.23	73,391.23
Log-Likelihood	-11,914.51	-17,401.91	-36,608.12
Root Mean Squared Error	15.48	11.80	10.41
Model 2			
Within-person (time-variant)			
Negative Emotion Transitions	4.70 [-1.79, 11.19]	3.77 [0.18, 7.36]*	1.95 [-0.50, 4.41]
Nestedness Subcomponent	1.82 [-2.53, 6.18]	5.77 [2.52, 9.01]***	1.25 [-1.02, 3.52]
Lagged Negative Emotion Intensity	0.33 [0.27, 0.39]***	0.33 [0.28, 0.38]***	0.34 [0.31, 0.37]***
Negative Emotion Transitions, Moderated by Baseline Depressive Symptoms[#]	-27.67 [-49.64, -5.69]*	-31.43 [-50.28, -12.59]**	-29.20 [-41.22, -17.18]***
(Bootstrapped 95% CI)	*[-53.21, -7.33]*	*[-46.24, -13.93]*	*[-43.12, -19.02]*
Nestedness Subcomponent, Moderated by Baseline Depressive Symptoms	-21.48 [-38.16, -4.80]*	-22.43 [-37.14, -7.71]**	-18.35 [-29.87, -6.83]**
Time Trend	0.03 [0.01, 0.06]*	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	10.71 [6.04, 15.38]***	6.40 [3.94, 8.85]***	9.63 [8.07, 11.20]***
Baseline Depressive Symptoms	40.70 [24.53, 56.87]***	32.60 [20.63, 44.57]***	24.30 [16.04, 32.57]***

Table S5

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Momentary Negative Emotion Intensity (*continued*)

	Estimates [95% Confidence Interval (CI)]		
Negative Emotion Transitions	10.16 [-21.47, 41.78]	-5.75 [-21.54, 10.05]	-18.73 [-30.46, -7.01]**
Nestedness Subcomponent	-41.71 [-56.34, -27.08]***	-23.68 [-34.41, -12.94]***	-25.52 [-32.42, -18.62]***
Bootstrapped confidence interval of the key (#) fixed effect	[-53.21, -7.33]	[-46.24, -13.93]	[-43.12, -19.02]
Akaike Information Criterion	23,856.78	34,789.72	73,211.38
Bayesian Information Criterion	24,096.04	35,047.43	73,499.76
Log-Likelihood	-11,888.39	-17,354.86	-36,565.69
Root Mean Squared Error	14.92	11.12	10.20

Note. Significant effects are displayed in bold. *n*: number of ESM assessments; *N*: number of young adults; #: key predictor variables central to hypothesis 1 and 2. Bootstrapped 95% confidence intervals (CI) were obtained with 1000 repetitions of bootstrapping.

**: p < .05; **: p < .01; ***: p < .001*

SUPPLEMENTAL MATERIAL 6: LEAVE-ONE-OUT SENSITIVITY ANALYSIS

As shown in Table S6.1, in 22 out of 26 possible leave-one-out conditions, the fixed effects key to our hypotheses remained statistically significant. The 26 conditions were given by 2 hypotheses times 13 emotion items (Dataset 1: 3, Dataset 2: 4, Dataset 3: 6). These results appeared to suggest that with more emotion items originally assessed, the impact of leaving one emotion out from analysis was smaller. These results also suggested that our main findings were not disproportionately contributed by transitions to, or from, a certain emotion.

Table S6.1

Estimates and Confidence Intervals of the Fixed Effects Key to the Two Hypotheses Under Different Conditions of Leaving one Emotion out from Analysis

	Fixed Effect [95% Confidence Interval]
Model 1 (Key Fixed Effect: Negative Emotion Transition Predicting Subsequent Emotion Intensity Change)	
Dataset 1	
Complete (nervous, downhearted, and distressed)	-3.05 [-6.03, -0.07]*
Excluding nervous	-0.96[-5.79, 3.87]
Excluding downhearted	-3.77[-7.42, -0.12]*
Excluding distressed	0.36[-3.25, 3.98]
Dataset 2	
Complete (angry, anxious, sad, depressed)	-3.89 [-6.31, -1.48]**
Excluding angry	-3.86[-6.82, -0.90]*
Excluding sad	-2.62[-4.86, -0.38]*
Excluding anxious	-3.77[-6.12, -1.42]**
Excluding depressed	-2.25[-4.51, 0.01]
Dataset 3	
Complete (angry, sad, anxious, depressed, stressed, lonely)	-3.41 [-5.02, -1.80]***
Excluding angry	-3.71[-5.28, -2.13]***
Excluding sad	-3.09[-4.65, -1.54]***
Excluding anxious	-3.57[-5.35, -1.80]***
Excluding depressed	-3.55[-5.21, -1.88]***
Excluding stressed	-1.45[-2.84, -0.06]*
Excluding lonely	-2.87[-4.47, -1.28]***

Table S6.1

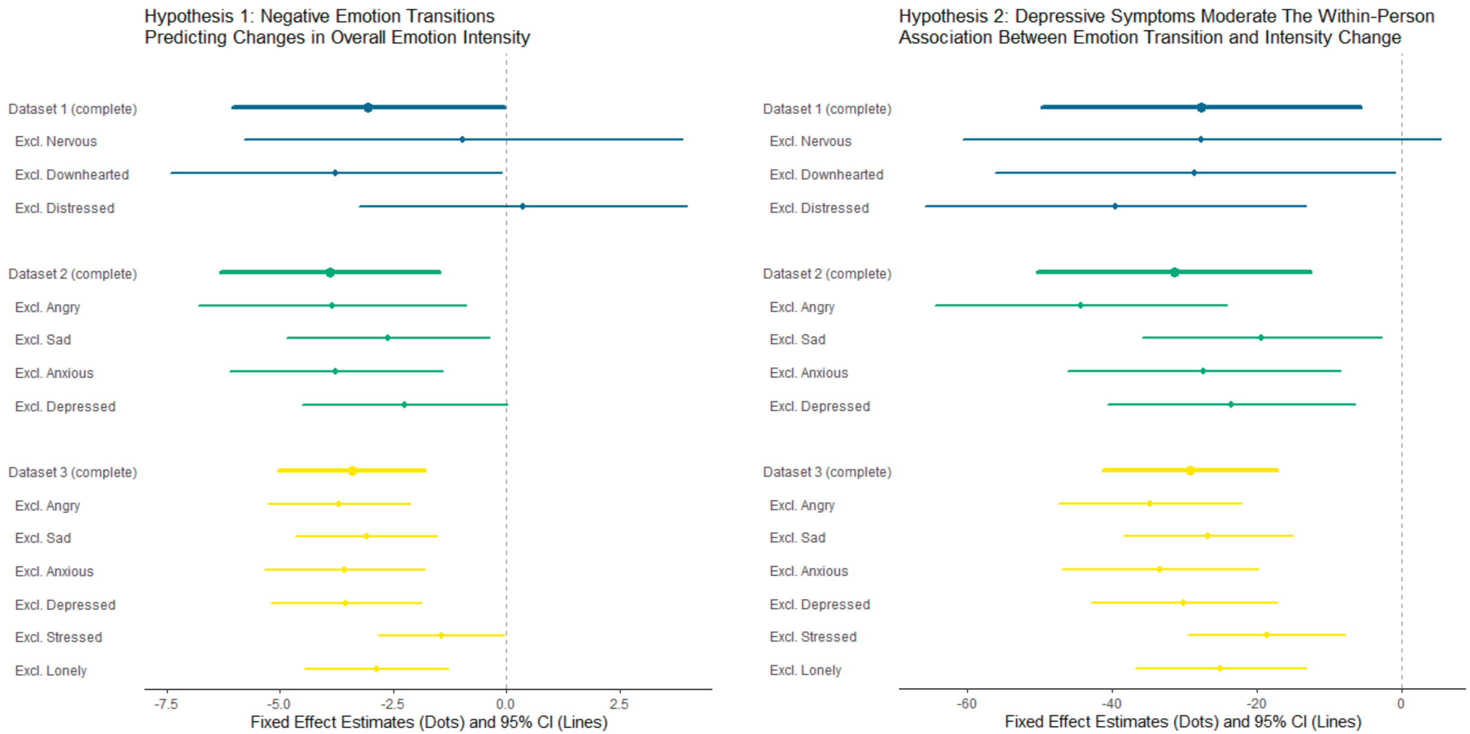
Estimates and Confidence Intervals of the Fixed Effects Key to the Two Hypotheses Under Different Conditions of Leaving one Emotion out from Analysis (*continued*)

	Fixed Effect [95% Confidence Interval]
Model 2 (Key Fixed Effect: The Moderating Effect of Baseline Depressive Symptoms on the Temporal Associations from Negative Emotion Transition to Subsequent Emotion Intensity Change)	
Dataset 1	
Complete (nervous, downhearted, and distressed)	-27.67 [-49.64, -5.69]*
Excluding nervous	-27.65[-60.70, 5.40]
Excluding downhearted	-28.59[-56.24, -0.93]*
Excluding distressed	-39.57[-65.85, -13.29]**
Dataset 2	
Complete (angry, anxious, sad, depressed)	-31.43 [-50.28, -12.59]**
Excluding angry	-44.36[-64.55, -24.17]***
Excluding sad	-19.32[-35.83, -2.80]*
Excluding anxious	-27.33[-46.22, -8.43]**
Excluding depressed	-23.56[-40.60, -6.52]**
Dataset 3	
Complete (angry, sad, anxious, depressed, stressed, lonely)	-29.20 [-41.22, -17.18]***
Excluding angry	-34.79[-47.47, -22.10]***
Excluding sad	-26.72[-38.43, -15.02]***
Excluding anxious	-33.40[-46.94, -19.86]***
Excluding depressed	-30.11[-42.96, -17.26]***
Excluding stressed	-18.68[-29.53, -7.82]***
Excluding lonely	-25.04[-36.84, -13.23]***

Note: *: p < .05; **: p < .01; ***: p < .001

Figure S6

Leave-One-Emotion-Out Sensitivity Analysis: Estimates and 95% CI



SUPPLEMENTAL MATERIAL 7: SENSITIVITY ANALYSES IN THREE ALTERNATIVE MODEL SPECIFICATIONS

Alternative Model Specification 1: Not Person-Centering Emotion-Transition

The purpose of person-centering the predictor variables, or separating within- and between-components, was to distinguish temporal fluctuations from individual differences. For instance, on a scale from 0 to 100, a momentary report of anger intensity of 20 from a young adult with an average level of 30 (momentarily *less angry* than usual) is qualitatively different if the momentary report is given by another young adult with an average level of 10 (momentarily *angrier* than usual). Thus, the raw score (such as 0) holds distinct meanings for each person. In our main analysis, we separated within- and between-components of negative emotion transition. Consequently, the analysis can be interpreted as whether heightened negative emotion transition, relative to each young adult's average, reduces negative emotion intensity.

Nevertheless, negative emotion transitions, based on the replacement subcomponent of Bray-Curtis dissimilarity, are calculated by contrasting current and previous assessments within the same individual, serving as a relative index where 0 means no transition and 1 indicates maximal transition. Thus, raw scores arguably carry the same meaning across individuals. Therefore, we tested an alternative model where negative emotion transitions are not person-centered. As shown in Table S6.2, fixed effects significant in the main analysis remained significant in this model , suggesting that our results are consistent regardless of whether heightened negative emotion transitions are relative to a person's average or assessed in absolute terms.

Table S7.1

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Momentary Negative Emotion Intensity with an Alternative Model Specification of not Centering the Nestedness and Replacement Subcomponents

	Estimates [95% Confidence Interval]		
Momentary Negative Emotion Intensity		Dataset	
Regressed on	1 ($N = 70$, $n = 2936$)	2 ($N = 94$, $n = 4651$)	3 ($N = 201$, $n = 10000$)
Model 1			
Within-person (time-variant)			
Negative Emotion Transitions#	-5.95 [-9.27, -2.64]***	-5.58 [-7.87, -3.30]***	-5.44 [-6.91, -3.98]***
Nestedness Subcomponent	-6.86 [-9.32, -4.39]***	-0.39 [-2.53, 1.74]	-2.94 [-4.40, -1.48]***
Lagged Negative Emotion Intensity	0.32 [0.26, 0.38]***	0.33 [0.28, 0.38]***	0.33 [0.30, 0.36]***
Time Trend	0.03 [0.01, 0.06]*	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	25.31 [21.34, 29.28]***	15.44 [12.85, 18.02]***	16.21 [14.73, 17.69]***
Model 2			
Within-person (time-variant)			
Negative Emotion Transitions	6.07 [-0.57, 12.71]	1.85 [-1.65, 5.35]	1.57 [-0.73, 3.87]
Nestedness Subcomponent	1.73 [-2.84, 6.29]	5.82 [2.44, 9.20]***	2.53 [0.11, 4.96]*
Lagged Negative Emotion Intensity	0.32 [0.26, 0.38]***	0.33 [0.28, 0.38]***	0.34 [0.30, 0.37]***
Negative Emotion Transitions, Moderated by Baseline Depressive Symptoms#	-37.86 [-60.33, -15.39]***	-27.94 [-46.21, -9.68]**	-32.72 [-44.75, -20.69]***
Nestedness Subcomponent, Moderated by Baseline Depressive Symptoms	-27.19 [-44.20, -10.19]**	-21.95 [-36.76, -7.14]**	-25.68 [-37.42, -13.94]***
Time Trend	0.03 [0.00, 0.06]*	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	6.83 [0.81, 12.85]*	4.66 [1.83, 7.48]**	8.16 [6.22, 10.09]***
Baseline Depressive Symptoms	59.36 [36.46, 82.26]***	41.99 [26.98, 57.01]***	38.17 [26.98, 49.36]***

Note. Significant effects are displayed in bold. *n*: number of ESM assessments; *N*: number of young adults; #: key predictor variables central to hypothesis 1 and 2. **: p < .05; **: p < .01; ***: p < .001*

Alternative Model Specification 2: Excluding the Nestedness Subcomponent as a Control Variable

Methodologically, Is It Acceptable to Analyze the Nestedness or Replacement Subcomponents as Independent Indices?

Researchers aiming to interpret the nestedness subcomponent must analyze it in conjunction with the replacement subcomponent. This is because the nestedness subcomponent technically does not directly measure nestedness; rather, it represents the nestedness of the measured dissimilarity. In other words, without including the replacement subcomponent—which contributes to the full Bray-Curtis dissimilarity—there is insufficient context to interpret the nestedness subcomponent effectively. Therefore, using the nestedness subcomponent as a standalone dissimilarity index is problematic (Almeida-Neto et al., 2012; MacGregor-Fors et al., 2022; Murray & Baselga, 2015). In contrast, it is acceptable to use the replacement subcomponent as an individual index (MacGregor-Fors et al., 2022). Indeed, the conceptual discussion of replacement subcomponent (Simpson, 1943) predates that of the Bray-Curtis dissimilarity (Sørensen, 1948). The Bray-Curtis dissimilarity started to be regularly used by ecologists since 1980s (e.g., Faith et al., 1987); it is only by 2001 that Lennon et al. (2001) recovered and formalized the calculation of the replacement subcomponent, which is subsequently named as the Simpson index of dissimilarity (Baselga, 2013b). The use of the Simpson dissimilarity index in the partitioning of the Bray-Curtis dissimilarity index into two subcomponents was only demonstrated relatively recently (Baselga, 2010, 2013b).

Analytical Rationale for the Alternative Specification in Excluding the Nestedness Subcomponent

The primary outcomes in our two hypotheses are the changes in overall negative emotion intensity. We assessed this by regressing negative emotion intensity on negative emotion transitions (t-1 → t) while controlling for the within-person component of lagged negative emotion intensity (t-1; or from the previous moment), which is a static account of how much the person deviated from their average level of negative emotion intensity at that time. In our main analysis, we included the nestedness subcomponent as a control variable, which accounts for absolute changes in the overall intensity of negative emotions from the previous to the current moment. This approach aligns with the existing applications of Bray-Curtis dissimilarity in psychological studies, where both subcomponents are used as predictor (control) variables. However, the nestedness subcomponent is conceptually related to our outcome in terms of magnitude of change, though not in direction. To check whether this potential issue has distorted our results, we reran our analyses without the nestedness subcomponent. The full model results are presented in Table S6.3. Compared to our main analyses, the fixed effects key to our hypotheses were no longer significant in Dataset 1. Dataset 1 was the dataset with the smallest sample size, and was thus understandably more sensitive to changes in model specifications.

Overall, we consider the results from this sensitivity analysis not contradicting those of the main analyses.

Table S7.2

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Momentary Negative Emotion Intensity with an Alternative Model Specification of Excluding the Nestedness Subcomponent

	Estimates [95% Confidence Interval]		
Momentary Negative Emotion Intensity Regressed on	Dataset		
	1 (*N* = 70, *n* = 2936)	2 (*N* = 94, *n* = 4651)	3 (*N* = 201, *n* = 10000)
Model 1			
Within-person (time-variant)			
Negative Emotion Transitions#	-0.78 [-3.39, 1.83]	-4.33 [-6.14, -2.51]***	-2.82 [-3.94, -1.70]***
Lagged Negative Emotion Intensity	0.35 [0.29, 0.40]***	0.37 [0.32, 0.41]***	0.36 [0.33, 0.39]***
Time Trend	0.03 [0.01, 0.06]*	0.00 [-0.01, 0.01]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	23.49 [20.02, 26.95]***	14.79 [12.71, 16.87]***	14.82 [13.64, 16.01]***
Negative Emotion Transitions	-38.72 [-98.73, 21.29]	-29.77 [-50.93, -8.60]**	-31.31 [-46.93, -15.69]***
Model 2			
Within-person (time-variant)			
Negative Emotion Transitions	3.23 [-2.73, 9.18]	-0.27 [-3.22, 2.67]	0.30 [-1.59, 2.18]
Lagged Negative Emotion Intensity	0.35 [0.29, 0.40]***	0.37 [0.32, 0.41]***	0.37 [0.33, 0.40]***
Negative Emotion Transitions, Moderated by Baseline Depressive Symptoms#	-14.56 [-33.92, 4.79]	-17.77 [-30.62, -4.91]**	-15.74 [-24.62, -6.85]***
Time Trend	0.03 [0.01, 0.06]*	0.00 [-0.01, 0.01]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	8.09 [3.32, 12.87]***	6.45 [3.94, 8.97]***	8.63 [6.96, 10.31]***
Baseline Depressive Symptoms	49.23 [29.87, 68.59]***	33.65 [21.20, 46.10]***	29.20 [20.04, 38.36]***
Negative Emotion Transitions	13.72 [-26.28, 53.71]	-19.07 [-34.43, -3.70]*	-24.91 [-38.05, -11.77]***

Note. Significant effects are displayed in bold. *n*: number of ESM assessments; *N*: number of young adults; #: key predictor variables central to hypothesis 1 and 2. **: p < .05; **: p < .01; ***: p < .001*

Alternative Model Specification 3: Controlling for Emotion Differentiation

Table S7.3

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables (Including Emotion Differentiation) in Multilevel Models

	Estimates [95% Confidence Interval (CI)]		
Momentary Negative Emotion Intensity Regressed on		Dataset	
	1 (*N* = 70, *n* = 2936)	2 (*N* = 94, *n* = 4651)	3 (*N* = 201, *n* = 10000)
Model 1			
Within-person (time-variant)			
Negative Emotion Transitions[#]	-2.74 [-5.63, 0.16]	-3.05 [-5.33, -0.78]**	-2.80 [-4.36, -1.25]***
Nestedness Subcomponent	-4.25 [-6.74, -1.75]***	0.72 [-1.70, 3.14]	-1.80 [-3.39, -0.21]*
Lagged Negative Emotion Intensity	0.32 [0.26, 0.38]***	0.42 [0.37, 0.48]***	0.38 [0.34, 0.42]***
Lagged Negative Emotion Differentiation	-0.21 [-0.45, 0.04]	0.18 [0.06, 0.29]**	0.08 [0.01, 0.14]*
Time Trend	0.04 [0.01, 0.06]**	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	23.10 [20.73, 25.47]***	15.14 [13.42, 16.85]***	14.98 [14.02, 15.93]***
Negative Emotion Transitions	-2.74 [-39.75, 34.28]	-15.95 [-35.25, 3.36]	-21.23 [-34.66, -7.79]**
Nestedness Subcomponent	-58.33 [-74.17, -42.49]***	-36.18 [-49.33, -23.04]***	-35.37 [-42.87, -27.87]***
Negative Emotion Differentiation	-8.23 [-13.43, -3.03]**	-6.10 [-9.00, -3.20]***	-3.06 [-4.09, -2.03]***
Model 2			
Within-person (time-variant)			
Negative Emotion Transitions	4.76 [-1.58, 11.10]	4.38 [0.57, 8.19]*	1.90 [-0.61, 4.41]
Nestedness Subcomponent	2.22 [-2.25, 6.69]	6.76 [2.72, 10.79]**	1.76 [-0.78, 4.31]
Lagged Negative Emotion Intensity	0.32 [0.25, 0.38]***	0.40 [0.35, 0.46]***	0.38 [0.34, 0.42]***
Negative Emotion Transitions, Moderated by Baseline Depressive Symptoms[#]	-26.78 [-48.10, -5.46]*	-34.15 [-53.26, -15.04]***	-26.66 [-38.87, -14.44]***
Nestedness Subcomponent, Moderated by Baseline Depressive Symptoms	-23.91 [-40.85, -6.96]**	-25.34 [-41.05, -9.62]**	-18.45 [-30.87, -6.02]**
Negative Emotion Differentiation	-0.24 [-0.48, 0.00]*	0.17 [0.05, 0.28]**	0.07 [0.01, 0.14]*
Time Trend	0.04 [0.01, 0.06]*	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	11.96 [7.23, 16.70]***	7.21 [5.03, 9.38]***	10.40 [8.86, 11.95]***

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables (Including Emotion Differentiation) in Multilevel Models (*continued*)

	Estimates [95% Confidence Interval (CI)]		
Negative Emotion Transitions	16.96 [-13.54, 47.46]	-6.02 [-19.82, 7.78]	-13.76 [-25.64, -1.88]*
Nestedness Subcomponent	-47.27 [-61.15, -33.39]***	-26.00 [-35.71, -16.29]***	-29.56 [-36.25, -22.86]***
Baseline Depressive Symptoms	35.01 [19.57, 50.44]***	31.02 [19.70, 42.35]***	21.47 [13.74, 29.20]***
Negative Emotion Differentiation	-6.15 [-10.70, -1.61]**	-4.71 [-6.90, -2.52]***	-2.60 [-3.51, -1.69]***

Note. Significant effects are displayed in bold. *n*: number of ESM assessments; *N*: number of young adults; #: key predictor variables central to hypothesis 1 and 2. **: p < .05; **: p < .01; ***: p < .001*

SUPPLEMENTAL MATERIAL 8: SENSITIVITY ANALYSES WITH TIME-LAGGED MODELS

In our main analyses, we focused on associations within the same hourly interval between two experience sampling method (ESM) assessments. This choice was informed by the closest existing evidence, particularly from psychotherapy research, which suggests that negative emotion transitions and reductions in intensity can unfold over a comparable time frame within a single therapy session. Accordingly, the main models examined concurrent associations between negative emotion transitions and changes in overall negative emotion intensity from t-1 to t.

To further probe the temporal ordering of these associations, we conducted time-lagged sensitivity analyses to retest H1 and H2. For these analyses, we created two lagged variables. Lagged negative emotion transition referred to the interval from t-2 to t-1. Lagged change in overall negative emotion intensity also referred to the interval from t-2 to t-1 and was calculated by subtracting person mean centered overall negative emotion intensity at t-2 from that at t-1. As in the main analyses, observations spanning overnight intervals were excluded.

We specified two sets of time-lagged models for each of the three datasets. In the first set, H1 tested whether negative emotion transitions in a prior interval (t-2 to t-1) predicted changes in overall negative emotion intensity in the subsequent interval (t-1 to t), and H2 tested whether depressive symptoms moderated this lagged association. These models were specified in the same way as the main models, except that the concurrent negative emotion transition variable was replaced by its lagged version.

In the second set, H1 tested whether changes in overall negative emotion intensity in a prior interval (t-2 to t-1) predicted negative emotion transitions in the subsequent interval (t-1 to t), and H2 tested whether depressive symptoms moderated this lagged association. In these models, negative emotion transition was specified as the outcome variable, and lagged change in overall negative emotion intensity was the main predictor. Unlike the main models, we did not control for lagged negative emotion intensity, because this information was already incorporated into the lagged change score. In addition, because negative emotion transition was now the outcome, it was no longer included as a predictor.

Across both sets of time-lagged models, all other specifications followed the main models, including controlling for the nestedness subcomponent and autocorrelated residuals. We also allowed random effects for all fixed effects. The only exception was in the second set of models, where we did not include a random effect for the nestedness subcomponent because doing so led to convergence problems in two of the three datasets.

As shown in Table S8.1 and Table S8.2, the fixed effects central to H1 and H2 were all non-significant. Overall, these sensitivity analyses did not support a clear temporal ordering between negative emotion transitions and changes in overall negative emotion intensity across lag intervals of 3 hours (in Datasets 2 and 3) and 6 hours (in Dataset 1).

Table S8.1

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Momentary Negative Emotion Intensity with an Alternative Model Specification of Using Lagged Negative Emotion Transitions

	Estimates [95% Confidence Interval]		
Momentary Negative Emotion Intensity		Dataset	
Regressed on	1 ($N = 67$, $n = 2103$)	2 ($N = 91$, $n = 3670$)	3 ($N = 198$, $n = 8057$)
Model 1			
Within-person (time-variant)			
Lagged Negative Emotion Transitions#	0.08 [-2.83, 2.99]	-0.37 [-2.09, 1.35]	-0.65 [-1.91, 0.61]
Nestedness Subcomponent	-1.54 [-3.39, 0.32]	0.26 [-1.17, 1.69]	-0.84 [-1.93, 0.25]
Lagged Negative Emotion Intensity	0.37 [0.30, 0.44]***	0.40 [0.35, 0.45]***	0.33 [0.30, 0.37]***
Time Trend	0.02 [-0.01, 0.05]	0.00 [-0.02, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	23.62 [20.81, 26.42]***	14.72 [12.81, 16.63]***	14.72 [13.67, 15.77]***
Negative Emotion Transitions	-4.61 [-55.22, 45.99]	-27.15 [-53.25, -1.05]*	-12.93 [-29.97, 4.12]
Nestedness Subcomponent	-70.02 [-90.40, -49.64]***	-33.40 [-51.01, -15.79]***	-40.02 [-49.92, -30.11]***
Model 2			
Within-person (time-variant)			
Negative Emotion Transitions	1.94 [-4.96, 8.85]	2.30 [-1.10, 5.71]	-1.73 [-4.32, 0.86]
Nestedness Subcomponent	1.84 [-2.73, 6.42]	0.06 [-2.95, 3.08]	-1.78 [-3.71, 0.16]
Lagged Negative Emotion Intensity	0.37 [0.30, 0.43]***	0.40 [0.35, 0.45]***	0.34 [0.31, 0.38]***
Lagged Negative Emotion Transitions, Moderated by Baseline Depressive Symptoms#	-6.58 [-29.77, 16.61]	-11.76 [-26.84, 3.31]	6.59 [-6.39, 19.57]
Nestedness Subcomponent, Moderated by Baseline Depressive Symptoms	-14.55 [-29.92, 0.82]	1.76 [-13.08, 16.61]	5.58 [-4.01, 15.16]
Time Trend	0.02 [-0.01, 0.05]	0.00 [-0.01, 0.02]	-0.03 [-0.04, -0.02]***
Between-person (time-invariant)			
Intercept	11.20 [5.85, 16.56]***	5.55 [2.96, 8.14]***	9.49 [7.90, 11.09]***
Negative Emotion Transitions	20.16 [-19.94, 60.27]	-10.05 [-27.23, 7.13]	-7.63 [-20.99, 5.73]
Nestedness Subcomponent	-55.66 [-72.96, -38.36]***	-25.62 [-37.34, -13.89]***	-29.78 [-37.53, -22.02]***
Baseline Depressive Symptoms	39.01 [21.59, 56.43]***	37.01 [24.61, 49.42]***	24.19 [15.53, 32.84]***

Note. *n*: number of ESM assessments; *N*: number of young adults; #: key predictor variables central to hypothesis 1 and 2. **: p < .05; **: p < .01; ***: p < .001*

Table S8.2

Fixed Effect Estimates of Within-Person and Between-Person Predictor and Control Variables in Multilevel Models that Predict Negative Emotion Transition with Lagged Change in Overall Negative Emotion Intensity

	Estimates [95% Confidence Interval]		
Momentary Negative Emotion Transition		Dataset	
Regressed on	1 (N = 67, n = 2103)	2 (N = 91, n = 3670)	3 (N = 198, n =8057)
Model 1			
Within-person (time-variant)			
Lagged Change in Overall Negative Emotion Intensity#	0.000 [-0.001, 0.000]	0.000 [-0.001, 0.000]	0.000 [-0.001, 0.000]
Nestedness Subcomponent	0.773 [0.749, 0.798]***	0.597 [0.575, 0.618]***	0.622 [0.608, 0.637]***
Time Trend	-0.001 [-0.001, 0.000]**	0.000 [-0.001, 0.000]	0.000 [-0.001, 0.000]**
Between-person (time-invariant)			
Intercept	0.396 [0.380, 0.411]***	0.413 [0.398, 0.428]***	0.407 [0.398, 0.415]***
Nestedness Subcomponent	1.086 [0.976, 1.196]***	1.286 [1.161, 1.411]***	1.155 [1.079, 1.232]***
Model 2			
Within-person (time-variant)			
Lagged Change in Overall Negative Emotion Intensity	0.000 [-0.001, 0.001]	0.001 [-0.001, 0.002]	0.000 [-0.001, 0.001]
Nestedness Subcomponent	0.798 [0.742, 0.854]***	0.541 [0.502, 0.579]***	0.618 [0.592, 0.644]***
Lagged Negative Emotion Intensity	-0.001 [-0.004, 0.002]	-0.003 [-0.006, 0.001]	-0.001 [-0.004, 0.002]
Lagged Change in Overall Negative Emotion Intensity, Moderated by Baseline Depressive Symptoms#	-0.095 [-0.281, 0.092]	0.261 [0.108, 0.414]***	0.024 [-0.092, 0.140]
Nestedness Subcomponent, Moderated by Baseline Depressive Symptoms	-0.001 [-0.001, 0.000]**	0.000 [-0.001, 0.000]	0.000 [-0.001, 0.000]**
Time Trend			
Between-person (time-invariant)	0.426 [0.388, 0.465]***	0.437 [0.411, 0.464]***	0.409 [0.392, 0.426]***
Intercept	1.076 [0.972, 1.180]***	1.221 [1.103, 1.340]***	1.153 [1.075, 1.231]***
Nestedness Subcomponent	-0.095 [-0.194, 0.003]	-0.104 [-0.174, -0.033]**	-0.009 [-0.072, 0.054]
Baseline Depressive Symptoms	0.000 [-0.001, 0.001]	0.001 [-0.001, 0.002]	0.000 [-0.001, 0.001]

Note. n: number of ESM assessments; N: number of young adults; #: key predictor variables central to hypothesis 1 and 2. **: $p < .05$; **: $p < .01$; ***: $p < .001$*

Appendix D

Supplemental Materials for Chapter 5 (Loneliness and Depressive Symptoms in Adolescents: A Multi-Timescale Examination)

SUPPLEMENTARY MATERIAL 1: EQUIVALENCE TESTING

1.1 Equivalence Between Adolescents Who Dropped-Out Before Wave 6 and Those Who Remained

In our study, there were more drop-outs since the COVID-19 pandemic. Specifically, the number of participating adolescents dropped from 667 in Wave 1 to 129 in Wave 6. To assess whether these subsamples were reasonably representative of the full sample in terms of their levels of loneliness and depressive symptoms, we conducted equivalence tests comparing Wave 1 scores of loneliness and depressive symptoms between adolescents who dropped-out before Wave 6 and those who remained. Two one-sided t-tests were used with an equivalence bound determined following Simonsohn (2015)'s "small telescope" approach, which was the smallest effect size that the sample had 33% power to detect.

Among the adolescents who dropped out, n = 565 had Wave 1 measurements of loneliness, and n = 558 had completed Wave 1 measurements of depressive symptoms. For the rest of the sample, n = 94 had completed these Wave 1 measurements. Using G*power (Faul et al., 2009), by specifying 33% power and a 0.05 significance level, we obtained that an appropriate equivalence bound is $d = \pm 0.16$ for the equivalence test between drop-out sample versus the non-drop-out sample.

Descriptive statistics on Wave 1 levels of loneliness and depressive symptoms in these samples are shown in Table S1. Results from two one-sided t-tests indicated that, within the specified equivalence bounds, the drop-out and non-drop-out samples were statistically equivalent on Wave 1 loneliness and depressive symptoms: Loneliness and depressive symptoms were equivalent with $t(115.4) = 1.73$, $p = .043$, and $t(118.9) = -2.99$, $p = .002$, respectively.

Table S1

Descriptive Statistics of Subsamples that Underwent Equivalence Tests

		Drop-out Throughout Six Waves		**H1a subsample that participated the ESM study**		**H2 subsample that participated Wave 5, ESM, or Wave 6**	
Wave 1 Measurements		Drop-out	Non Drop-Out	H1a subsample	The rest of the sample	H2 subsample	The rest of the sample
Loneliness	*n*	565	94	71	588	140	519
	M (SD)	0.37 (0.44)	0.43 (0.53)	0.40 (0.50)	0.38 (0.45)	0.37 (0.48)	0.39 (0.45)
Depressive Symptoms	*n*	558	94	71	581	140	512
	M (SD)	0.48 (0.39)	0.50 (0.44)	0.46 (0.42)	0.49 (0.39)	0.48 (0.41)	0.49 (0.39)

1.2 The Representativeness of Subsamples in Analyzing Hypothesis 1a (n = 84) and Hypothesis 2 (n = 181)

The experience sampling method (ESM) study design required us to recruit adolescents and parents as dyads. This, together with participant drop-outs throughout the six waves of longitudinal study, resulted in relatively small subsamples out of the full sample (N = 774). Specifically, Hypothesis 1a (H1a, hourly feedback loop between loneliness and depressive symptoms) included $n = 84$ adolescents who participated in the ESM study; Hypothesis 2 (H2, across-time-scale influence) included $n = 181$ adolescents who provided data at Wave 5, the ESM study, or Wave 6.

To assess whether these subsamples were reasonably representative of the full sample in terms of their levels of loneliness and depressive symptoms, we conducted equivalence tests comparing Wave 1 scores of loneliness and depressive symptoms between each subsample and the remainder of the sample. Two one-sided t-tests were used with equivalence bounds determined following Simonsohn (2015)'s recommendation, which was the smallest effect size that the sample had 33% power to detect.

Among the H1a subsample ($n = 84$), $n = 71$ had completed Wave 1 measurements of loneliness and depressive symptoms. For the rest of the sample, $n = 588$ had provided Wave 1 loneliness, and $n = 581$ had provided Wave 1 depressive symptoms. Using G*power, by specifying 33% power and a 0.05 significance level, we obtained that an appropriate equivalence bound is $d = \pm0.19$ for the equivalence test between H1a subsample versus the rest the sample.

Among the H1b subsample (N = 181), $n = 140$ had completed Wave 1 measurements of loneliness and depressive symptoms. For the rest of the sample, $n = 519$ had provided Wave 1 loneliness, and $n = 512$ had provided Wave 1 depressive symptoms. Using G*power, by specifying 33% power and a 0.05 significance level, we obtained that an appropriate equivalence bound is $d = \pm0.14$ for the equivalence test between the H2 subsample versus the rest the sample.

Descriptive statistics on Wave 1 levels of loneliness and depressive symptoms in these subsamples are shown in Table S1. Results from two one-sided t-tests indicated that, within the specified equivalence bounds, both the H1a and H2 subsamples were statistically equivalent to the remainder of the sample on Wave 1 loneliness and depressive symptoms. For the H1a subsample, loneliness and depressive symptoms were equivalent with $t(84.33) = 2.71$, $p = .004$, and $t(85.48) = -2.98$, $p = .002$, respectively. For the H2 subsample, equivalence was also supported with $t(209.7) = -2.83$, $p = .003$ for loneliness, and $t(214.8) = -3.38$, $p < .001$ for depressive symptoms.

These findings suggested that the subsamples used to test Hypotheses 1a and 2 did not differ meaningfully from the rest of the sample in their initial levels of loneliness and depressive symptoms.

SUPPLEMENTARY MATERIAL 2:

SUITABILITY OF ANALYZING TRAIT LONELINESS AND DEPRESSIVE SYMPTOMS ACROSS WAVES

To ensure the suitability of analyzing trait loneliness and depressive symptoms across five waves (Waves 1, 3, 4, 5, and 6), we conducted two sets of analyses: (1) multilevel confirmatory factor analysis (MCFA) to assess factor structure stability between and within adolescents, as pre-registered, and (2) a longitudinal invariance test encompassing all waves, to assess if factor structures at different waves are comparable.

2.1. Multilevel Confirmatory Factor Analysis

Consistent with procedures commonly used in experience sampling research (e.g., Eisele et al., 2021), we conducted MCFA separately for loneliness and depressive symptoms items, clustering data within individuals. This approach assessed the factor structure at both the within-adolescent and between-adolescent levels. Each set of items (e.g., 10 CES-D items for depressive symptoms, 12 LEKA items for loneliness) loaded onto a single respective latent factor.

Model fit was evaluated using conventional cut-off criteria: RMSEA < .08, CFI > .95, and TLI > .90 (Bentler & Bonett, 1980; Schermelleh-Engel et al., 2003). As the within-adolescent model for loneliness initially failed to meet the TLI threshold, we checked the modification indices to identify overlapping items. We then allowed residuals of overlapping items to correlate (items 9 and 10, and items 11 and 12), improving model fit. Final fit indices (see Table S2.1) were satisfactory, supporting the unidimensionality of both scales. Thus, using mean scores of the respective scales for main analyses was considered appropriate, as pre-registered.

Table S2.1

Multilevel Confirmatory Factor Analysis of Loneliness and Depressive Symptoms

	Standardized factor loading						
Variable	Min	Max	Median	$\chi 2$	RMSEA	CFI	TLI
Loneliness							
Within-adolescent model*	0.46	0.67	0.61	404.99	0.06	0.97	0.91
Between-adolescent model	0.72	0.98	0.92	151.97	0.03	0.99	0.98
Depressive symptoms							
Within-adolescent model	0.20	0.69	0.50	220.78	0.05	0.96	0.91
Between-adolescent model	0.52	1.00	0.81	113.19	0.03	0.98	0.96

Note. *We included correlations between residual variances of two pairs of overlapping loneliness items: item 9 (“I feel abandoned by my friends”) and 10 (“I feel pushed aside by my friends”), and item 11 (“I’m sad because no one wants to join me”) and 12 (“I’m sad because I don’t have any friends”).

2.2. Longitudinal Invariance Between the First and Last Measurement

We conducted longitudinal invariance testing to check whether the factor structures of LEKA (loneliness) and CES-D (depressive symptoms) were held across waves. For loneliness, we ran the test twice: one including all 12 items, and another excluding item 7 ("I feel alone at school"), which was omitted for two participants at Wave 6 who were no longer in school. For depressive symptoms, we ran just one test, because the same items were used across all participants across waves. We applied conventional change thresholds (Δ) in fit indices: ΔRMSEA < .015, ΔCFI > -.01, and ΔSRMR < .015 (F. F. Chen, 2007).

Results are reported in Table S2.2. Changes in all fit indices supported metric invariance (equal factor loadings) and scalar invariance (equal factor loadings and intercepts). This indicated that we could compare the mean score of the two scales of loneliness and depressive symptoms across time.

Table S2.2

Change of Fit Indices in Increasingly Constrained Models that Implied Increasing Degrees of Measurement Invariance

Change (Δ) of Fit Indices	**Metric Invariance**	**Scalar Invariance**	**Strict Invariance**
Loneliness (all items)			
ΔRMSEA	**0.000**	**0.000**	**0.003**
ΔSRMR	**0.002**	**0.000**	**0.005**
ΔCFI	**-0.005**	**-0.010**	-0.037
Loneliness (item 7 excluded)			
ΔRMSEA	**0.000**	**0.000**	**0.003**
ΔSRMR	**0.003**	**0.001**	**0.006**
ΔCFI	**-0.006**	**-0.009**	-0.036
Depressive Symptoms			
ΔRMSEA	**0.000**	**0.000**	**0.003**
ΔSRMR	**0.004**	**0.002**	**0.004**
ΔCFI	**-0.006**	**-0.007**	-0.033

Note. In evaluating a model, higher values of CFI are better, whereas lower values of RMSEA and SRMR are better. Fit indices changes in line of conventional thresholds of ΔRMSEA < .015, ΔCFI > -.01, and ΔSRMR < .015 (F. F. Chen, 2007) are denoted in bold.

SUPPLEMENTAL MATERIAL 3: FULL MODEL SPECIFICATIONS

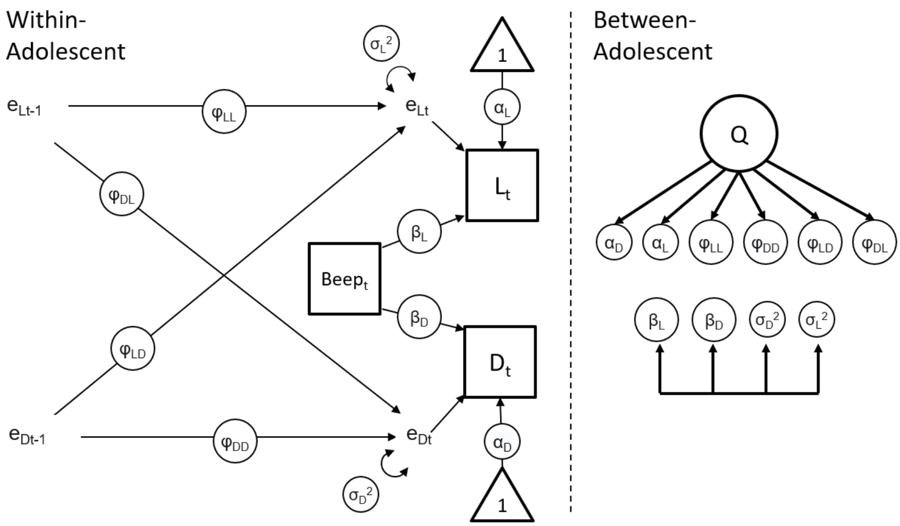
In our preregistration, we have stated the steps in determining: (1) whether there are substantial time trends in outcome variables, which affected our choice of analyzing the data with either dynamic structural equation modeling (DSEM) or residual dynamic structural equation modeling (RDSEM), and (2) how to proceed when models did not converge with the default option of unconstrained covariance structure where all random effects covariate in pairs. For clarity, we first present our full model specifications (Section 3.1), before we show the steps we have taken to arrive at our final model specifications with regards to the two issues of time trend (Section 3.2.1) and model convergence (Section 3.2.2).

3.1. Final Model Specifications

In Figure S3.1.1a (Model 1a: hourly relations), S3.1.1b (Model 1b: half-yearly relations), and S3.1.2 (Model 2: across-timescale effects), we graphically illustrate the final model specifications in the Mplus analysis scripts we have used.

Figure S3.1.1a

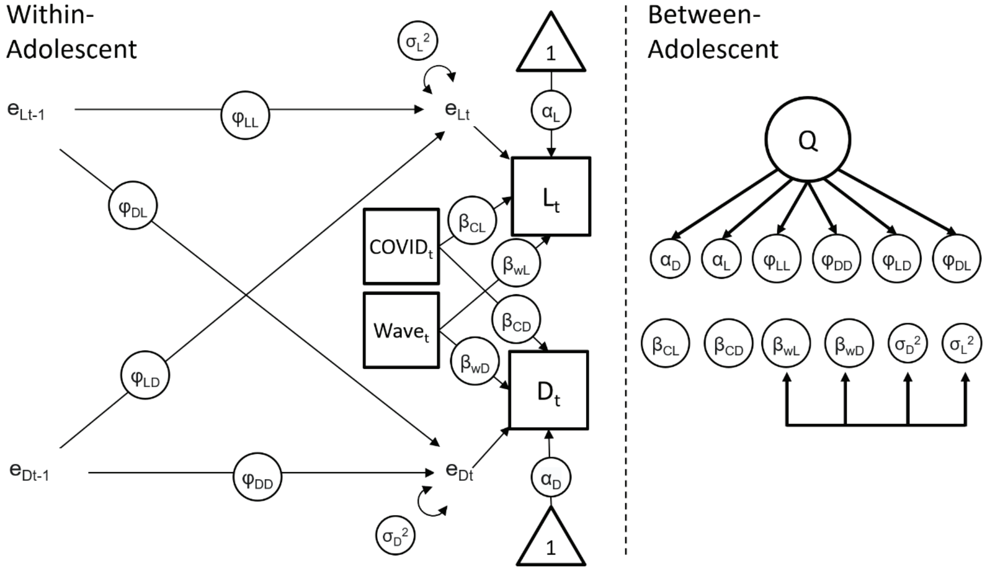
Full Specifications of Model 1a (Hourly Relations Controlled for the time trend throughout the ESM study).



Note. D: Depressive Symptoms; L: Loneliness; e: Residual; α, β, φ: person-specific estimates of within-person paths (i.e., random intercepts and random slopes); σ: person-specific estimates of residual variances; Q: common factor of person-specific estimates (random effects); Beep: The number of the current ESM observation (1, 2, …70); t: current observation; t-1: previous observation; Subscripts LL, LD, DL, DD that followed φ: combinations of temporal relations within and between loneliness and depressive symptoms. Unidirectional arrows in the between-adolescent side: factor analytic covariance structure. Bidirectional and overlapping arrows in the between-adolescent side: pairs of covariance.

Figure S3.1.1b

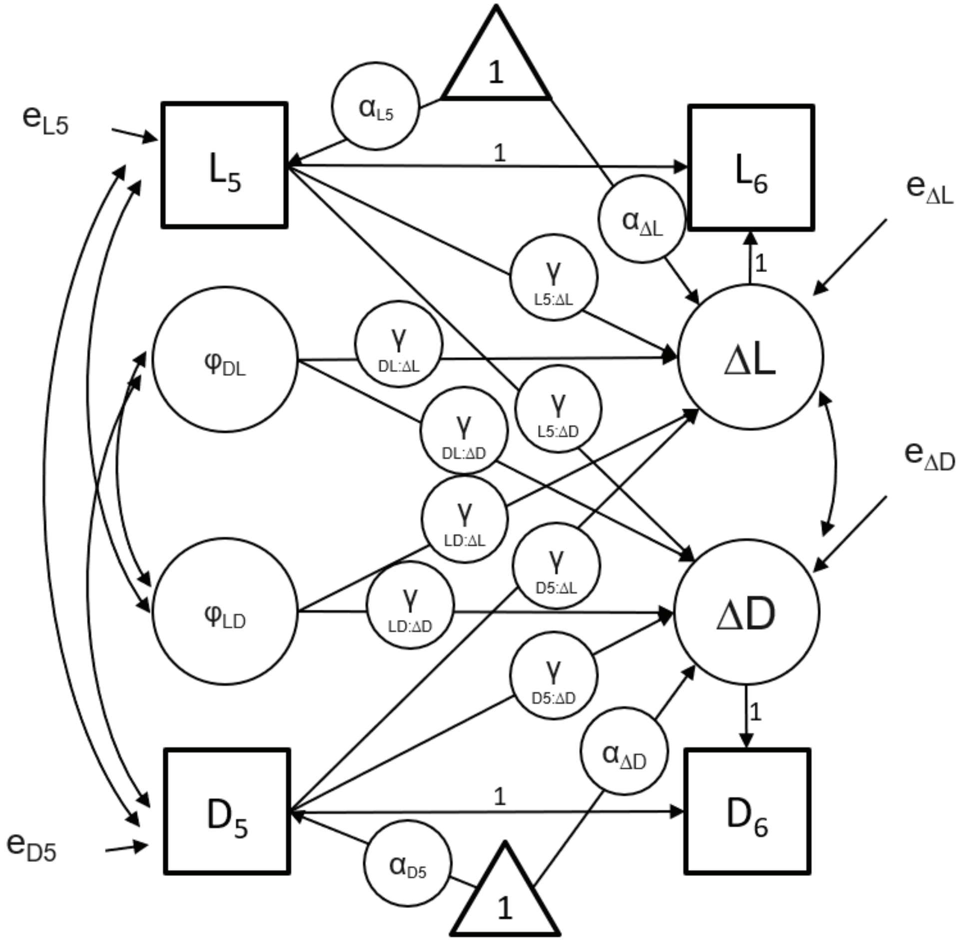
Full Specifications of Model 1b (Half-Yearly Relations Controlling for the Time Trend Throughout the Longitudinal Study and the COVID-19 Related Time Trend.



Note. D: Depressive Symptoms; L: Loneliness; e: Residual; α, β, φ: person-specific estimates of within-person paths (i.e., random intercepts and random slopes); σ: person-specific estimates of residual variances; Q: common factor of person-specific estimates (random effects); t: current observation; t-1: previous observation; Subscripts LL, LD, DL, DD that followed φ: combinations of temporal relations between loneliness and depressive symptoms. Subscripts wL, wD, CL, CD that followed β: wave-specific (w) or COVID-specific (C) time trends to loneliness (L) or depressive symptoms (D); Unidirectional arrows in the between-adolescent side: factor analytic covariance structure. Bidirectional and overlapping arrows in the between-adolescent side: pairs of covariance.

Figure S3.1.2

Full Specifications of Model 2 (Across-Timescale Effects).



Note. D: Depressive Symptoms; L: Loneliness; ΔD: Latent change in Depressive Symptoms; ΔL Latent change in Loneliness; e: Residual; α: mean/intercept; φ: person-specific estimates of within-person temporal relations extracted from Model 1a; γ: path estimate (":" denotes an effect, e.g., $\gamma_{D5:\Delta D}$ denotes the path estimate of the effect from D_5 to ΔD); Subscript 5, 6: Measured at Wave 5 or Wave 6.

3.2. Specifications of Model 1a and 1b

3.2.1. Within-Adolescent Level Specifications of Model 1a and 1b in View of Time Trends

To test the hourly and half-yearly feedback loops (H1a and H1b), we used experience sampling method (ESM) data, up to 70 beeps per adolescent, and panel data, spanning up to 5 waves of measurement per participant. Loneliness and depressive symptoms, our key variables, may systematically change over time with increasing beeps or waves. To assess whether within-person variance in these variables was attributable to time trends, we estimated models with only the intercept and time variables (beeps or waves) as predictors (e.g., beep number 1 to 70 in predicting momentary loneliness). We ran four such models, one for each measure of trait and state loneliness and depressive symptoms, allowing for random intercepts and random slopes of time. This approach captured both baseline levels of loneliness/depressive symptoms and individual differences in time trends of loneliness and depressive symptoms.

Using the r2mlm R package (Shaw et al., 2022), we calculated the proportion of within-person variance explained by time trends. Time trends accounted for substantial proportions of within-adolescent variance in loneliness (5% in half-yearly data and 9% in hourly data) and depressive symptoms (14% in half-yearly data and 13% in hourly data). These proportions exceeded the 5% pre-registered threshold. Accordingly, we used residual dynamic structural equation modeling (RDSEM) instead of DSEM to account for these time trends.

In RDSEM, time trend variables were included so that residuals represented deviations from modelled trends in loneliness and depressive symptoms. To visualize these trends, we plotted time series for loneliness and depressive symptoms in hourly and half-yearly time scales (Figures S3.2.1 and S3.2.2). Most trends were approximately linear, except trait loneliness, which appeared stable or declining initially but began to rise from Wave 4 onward.

For Model 1a (hourly relations; ESM data), we conducted RDSEM using ESM beep as the time trend variable. In Model 1b (half-yearly relations, panel data), Wave 4, the time point which trait loneliness began to rise, coincided with the COVID-19 pandemic. Prior studies have documented the impact of the COVID-19 pandemic on adolescent social and mental health (van den Boom et al., 2023). To account for this, we applied a piecewise growth modeling approach (Pouwels et al., 2021) with two time variables: $WaveR_t$, indexing time since study started, and $COVID_t$, indexing time since the pandemic began. Using $WaveR_t$ and $COVID_t$, we could model the time trends of loneliness and depressive symptoms as a function of time elapsed since the study has started ($WaveR_t$) and since the COVID-19 pandemic has come in place ($COVID_t$).

For $WaveR_t$, we coded t = -4 at Wave 1 (fall 2017), then increment it every half a year so that t = 0 right before the COVID-19 pandemic (fall 2019) and t = 4 at Wave 6 (fall 2021). To represent the full nine half-yearly points from fall 2017 to fall 2021, we inserted empty rows with missing values for intermediate points so that $WaveR_t$ was indexed as (-4, -3, -2, -1, 0, 1, 2, 3, 4). For $COVID_t$, we coded 0 for all pre-pandemic observations (up to fall 2019) and 1–4 for post-pandemic half-years, so that it was indexed as (0, 0, 0, 0, 0, 1, 2, 3, 4). $COVID_t$ = 1 at the measurement at spring 2021, when COVID-19 restrictions first came in place. This way of coding ensured that the COVID-19 time variable had no influence on loneliness and depressive symptoms before the COVID-19 pandemic happened.

In RDSEM, loneliness and depressive symptoms were regressed on both $WaveR_t$ and $COVID_t$. The intercepts of loneliness and depressive symptoms (t = 0 for both time trend variables) reflected mean levels right before the COVID-19 pandemic. The slopes of $WaveR_t$ (β_{wL}, β_{wD}, Figure S3.1.b) captured normative half-yearly change, and the slopes of $COVID_t$ (β_{CL}, β_{CD}) represented COVID-specific changes above and beyond those trends. Both slopes were modeled as random effects, allowing for individual differences in the slopes between adolescents.

Figure S3.2.1

Time Trend of Loneliness and Depressive Symptoms in the ESM Study

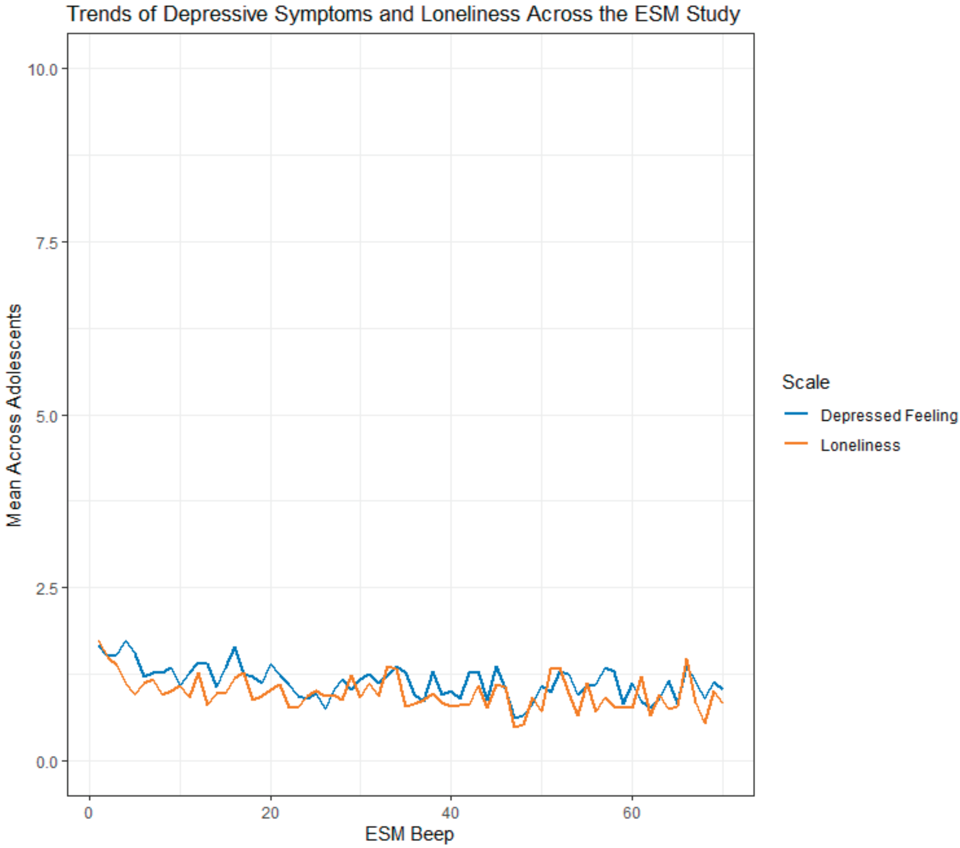
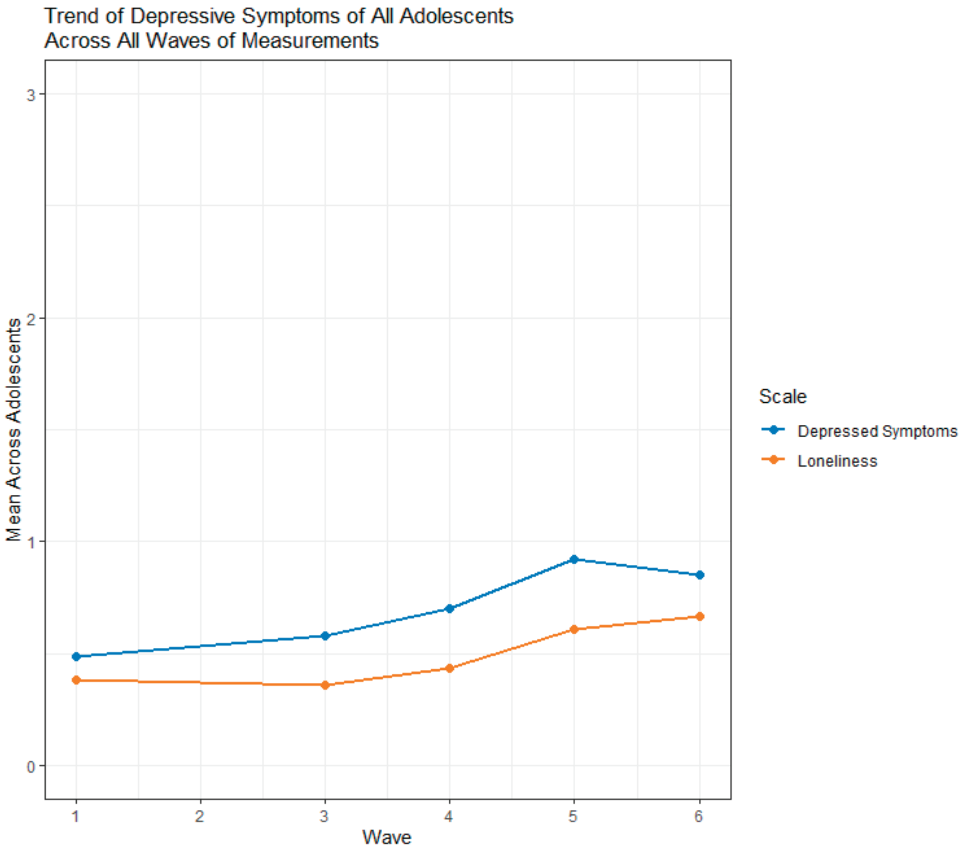


Figure S3.2.2

Time Trend of Loneliness and Depressive Symptoms in the Longitudinal Study



Note. Data from Wave 4 to 6 were collected during the COVID-19 pandemic.

We adapted the pre-registered bivariate multilevel vector autoregressive model (p. 626, McNeish & Hamaker, 2020) using RDSEM specifications (p. 629, McNeish & Hamaker, 2020). The within-adolescent structures for Model 1a and Model 1b are shown in Figures S3.1.1a and S3.1.1b. Model 1a included the ESM beep number as the sole time trend predictor; Model 1b included both the wave number and the COVID-19-time variable.

3.2.2. Between-Adolescent Level Specifications of Model 1a and 1b That Enabled Stable Model Convergence

Our pre-registration specified that person-specific parameters (i.e., random effects) should be freely estimated with all possible covariances (e.g., between the random intercepts of loneliness and depressive symptoms). However, this full covariance structure led to non-convergence in both Model 1a and 1b. To address this, we followed two pre-registered principles for simplifying the covariance structure: (1) applying a factor analytic covariance structure, and (2) progressively removing covariances between person-specific parameters starting with those not central to our hypotheses (e.g., covariances with person-specific residual variances). The factor analytic structure is an approach that decomposes random effect covariance matrices into loadings and uniquenesses, so as to improve numerical stability and avoiding nonpositive definiteness during model estimation (McNeish & Bauer, 2022).

Following these principles, we simplified Model 1a and 1b step-by-step (see Table S3) until stable convergence was achieved. Stable convergence was confirmed by doubling the number of iterations of the first convergence, inspecting the smoothness of posterior density plots, and examining trace plots of the Bayesian posterior estimates.

Table S3

Stepwise Simplification Of Model Covariance Structure Before Reaching Model Convergence

	Model 1a		Model 1b	
Covariance Structure Between Person-Specific Estimates	Main Analysis	Sex Difference	Main Analysis	Sex Difference
Unrestricted covariance structure (i.e., having covariance between every possible pairs of person-specific estimates)	N	-	N	-
Factor analytic structure covering all random effects	N	-	N	-
Factor analytic structure covering α, β, and φ, then allowing a pair of σ to covary	N	-	N	-
Factor analytic structure covering α, β, and φ (the remaining pair of σ does not covary)	N	-	N	-
Factor analytic structure covering α and φ, and unrestricted covariance structure between all possible pairs between β and σ	Y	Y	Y	N
Factor analytic structure covering α and φ, then allowing a pair of β to covary and a pair of σ to covary (but β and σ do not covary)	-	-	-	N
Factor analytic structure covering α and φ, then allowing a pair of σ to covary (but the pair of β does not covary nor does it covary with σ)	-	-	-	N
Factor analytic structure covering α and φ, then allowing pairs of β to covary (but the pair of σ does not covary nor does it covary with β)	-	-	-	Y

Note. α: intercepts, β: time trends, φ: temporal relations (e.g., lonely->depressed), σ: residual variances N: Non-convergence. Y: Convergence. -: Did not estimate because either (i) the model converged in earlier steps or (ii) exploratory models including sex variables were more complicated than their main models, so the covariance structures with which the main model did not converge were not attempted.

3.3. Specifications of Model 2

Model 2 specifications largely followed our pre-registration, with one minor deviation: we set *starting values*, rather than *fixed values*, for the covariances between predictor variables (i.e., between φ_{LD} and φ_{DL}, and between L_5 and D_5, Figure S3.1.2). This adjustment was necessary to enable Mplus's default estimation algorithm (ALGORITHM = GIBBS(PX1)). This adjustment also allowed the covariances in the Hypothesis 2 subsample (n = 181) to differ from those estimated in Model 1a (n = 84) and Model 1b (n = 774), which was conceptually appropriate given the different (sub)samples used.

SUPPLEMENTAL MATERIAL 4: FULL MODEL RESULTS AND INSPECTIONS OF THE STABILITY OF PARAMETER ESTIMATES

In this Supplemental Material, we first present standardized estimates of model results. Then, we present trace plots and density plots on the key parameters or paths we have estimated (e.g., the hourly Lonely→Depressed temporal relation in Model 1a).

4.1. Standardized Estimates of Model 1a, Model 1b, Model 2, and Their Corresponding Exploratory Models on Potential Sex Differences

Table S4.1.a

Standardized Estimates in Model 1a (Hourly): Main, Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences

	Standardized Estimates (95% Credibility Interval)	
	Pre-registered Analysis	Exploratory Analysis (Sex Differences)
	n = 84	n_{boys} = 36, n_{girls} = 48
Within-adolescent		
Lonely→Depressed (φ_{LD})	0.094 (0.049, 0.139)	0.101 (0.056, 0.144)
Depressed→Lonely (φ_{DL})	0.072 (0.031, 0.113)	0.065 (0.017, 0.110)
Lonely→Lonely (φ_{LL})	0.197 (0.142, 0.243)	0.196 (0.145, 0.248)
Depressed→Depressed (φ_{DD})	0.231 (0.184, 0.277)	0.205 (0.157, 0.253)
Time Trend: Loneliness (β_L)	-0.150 (-0.238, -0.096)	-0.197 (-0.315, -0.132)
Time Trend: Depressive Symptoms (β_D)	-0.144 (-0.294, -0.085)	-0.188 (-0.464, -0.103)
Residual Variance: Loneliness (σ_L)	0.822 (0.792, 0.856)	0.795 (0.764, 0.830)
Residual Variance: Depressive Symptoms (σ_D)	0.781 (0.751, 0.811)	0.747 (0.712, 0.780)
Between-adolescent		
Factor analytic covariance structure		
Factor loading: Intercept (Lonely)	0.942 (0.814, 0.998)	0.000 (-0.974, 0.944)
Factor loading: Intercept (Depressed)	0.927 (0.797, 0.995)	0.000 (-0.989, 0.930)
Factor loading: Lonely→Lonely	0.178 (-0.213, 0.544)	0.000 (0.000, 0.000)
Factor loading: Depressed→Depressed	0.090 (-0.277, 0.441)	0.000 (-0.977, 0.984)
Factor loading: Lonely→Depressed	0.319 (-0.115, 0.688)	0.000 (-0.293, 0.318)
Factor loading: Depressed→Lonely	0.567 (-0.280, 0.972)	0.011 (-0.964, 0.970)
Sex differences: female-specific estimates of		
Lonely→Depressed (φ_{LD})	-	0.138 (-0.113, 0.368)
Depressed→Lonely (φ_{DL})	-	0.006 (-0.373, 0.487)

Table S4.1.a

Standardized Estimates in Model 1a (Hourly): Main, Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences (*continued*)

	Standardized Estimates (95% Credibility Interval)	
Residual variance (loneliness), covary with		
Residual variance (depressed)	0.382 (0.161, 0.566)	0.398 (0.170, 0.582)
Time trend (loneliness)	-0.074 (-0.378, 0.226)	-0.011 (-0.333, 0.292)
Time trend (depressed)	0.040 (-0.271, 0.345)	0.296 (-0.105, 0.566)
Residual variance (depressed), covary with		
Time trend (loneliness)	-0.077 (-0.372, 0.246)	0.101 (-0.237, 0.425)
Time trend (depressed)	0.027 (-0.275, 0.316)	0.147 (-0.271, 0.458)
Time trend (loneliness), covary with		
Time trend (depressed)	0.857 (0.551, 0.965)	0.609 (0.247, 0.883)
Means or Intercepts,		
Lonely	1.074 (0.792, 1.367)	1.110 (0.804, 1.416)
Depressed	1.132 (0.847, 1.429)	1.162 (0.854, 1.476)
Lonely→Lonely	0.714 (0.397, 1.066)	0.607 (0.290, 0.948)
Depressed→Depressed	0.896 (0.547, 1.288)	0.830 (0.473, 1.244)
Lonely→Depressed	0.518 (0.143, 0.920)	0.097 (-0.263, 0.476)
Depressed→Lonely	0.760 (0.222, 1.437)	0.366 (-0.386, 1.113)
Time trend (loneliness)	-0.538 (-1.010, -0.160)	-0.472 (-0.938, -0.108)
Time trend (depressed)	-0.482 (-0.886, -0.111)	-0.300 (-0.719, 0.036)
Log Residual Variance (Loneliness)	-0.179 (-0.397, 0.038)	-0.187 (-0.407, 0.036)
Log Residual Variance (Depressed)	-0.154 (-0.372, 0.064)	-0.180 (-0.399, 0.039)
Unexplained Variance,		
Lonely	0.113 (0.003, 0.337)	1.000 (0.033, 1.000)
Depressed	0.141 (0.009, 0.365)	1.000 (0.017, 1.000)
Lonely→Lonely	0.963 (0.704, 1.000)	1.000 (1.000, 1.000)
Depressed→Depressed	0.980 (0.802, 1.000)	0.426 (0.020, 1.000)
Lonely→Depressed	0.897 (0.526, 1.000)	0.969 (0.798, 1.000)
Depressed→Lonely	0.677 (0.055, 0.999)	0.369 (0.017, 0.988)

Note. -: a path not included in the analysis model, hence no estimates.

Table S4.1.b

Standardized Estimates in Model 1b (Half-yearly): Main, Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences

	Standardized Estimates (95% Credibility Interval)	
	Pre-registered Analysis	Exploratory Analysis (Sex Differences)
	$N = 774$	$N_{boys} = 364$, $N_{girls} = 410$
Within-adolescent		
Lonely→Depressed (φ_{LD})	0.028 (0.013, 0.044)	0.029 (0.019, 0.043)
Depressed→Lonely (φ_{DL})	0.023 (0.012, 0.038)	0.029 (0.014, 0.045)
Lonely→Lonely (φ_{LL})	0.925 (0.907, 0.938)	0.916 (0.895, 0.933)
Depressed→Depressed (φ_{DD})	0.922 (0.906, 0.935)	0.919 (0.903, 0.934)
Time Trend: Loneliness (β_L)	-0.452 (-0.548, -0.345)	-0.408 (-0.507, -0.312)
Time Trend: Depressive Symptoms (β_D)	0.040 (-0.067, 0.150)	0.084 (-0.042, 0.179)
COVID-19 Trend: Loneliness (β_{CL})	0.669 (0.509, 0.797)	0.586 (0.447, 0.730)
COVID-19 Trend: Depressive Symptoms (β_{CL})	0.182 (-0.010, 0.337)	0.118 (-0.025, 0.323)
Residual Variance: Loneliness (σ_L)	0.101 (0.085, 0.119)	0.108 (0.091, 0.126)
Residual Variance: Depressive Symptoms (σ_D)	0.095 (0.080, 0.117)	0.097 (0.085, 0.110)
Between-adolescent		
Factor analytic covariance structure		
Factor loading: Intercept (Lonely)	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)
Factor loading: Intercept (Depressed)	0.000 (-0.969, 0.717)	0.000 (-0.567, 0.821)
Factor loading: Lonely→Lonely	0.000 (-1.212, 1.102)	0.000 (-0.975, 1.523)
Factor loading: Depressed→Depressed	0.000 (-1.283, 1.098)	0.000 (-1.035, 2.467)
Factor loading: Lonely→Depressed	0.000 (-1.252, 1.198)	0.000 (-1.456, 1.252)
Factor loading: Depressed→Lonely	0.000 (-1.026, 1.493)	0.000 (-1.269, 1.108)
Sex differences: female-specific estimates of		
Lonely→Depressed (φ_{LD})	-	0.010 (-0.460, 0.429)
Depressed→Lonely (φ_{DL})	-	0.100 (-0.287, 0.539)
Residual variance (loneliness), covary with		
Residual variance (depressed)	0.795 (0.676, 0.910)	-
Time trend (loneliness)	0.398 (0.286, 0.503)	-
Time trend (depressed)	0.266 (0.122, 0.391)	-
Residual variance (depressed), covary with		
Time trend (loneliness)	0.299 (0.172, 0.410)	-
Time trend (depressed)	0.360 (0.223, 0.478)	-
Time trend (loneliness), covary with		
Time trend (depressed)	0.370 (0.252, 0.484)	0.391 (0.266, 0.507)
COVID-19 trend (loneliness), covary with		

Table S4.1.b

Standardized Estimates in Model 1b (Half-yearly): Main, Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences (*continued*)

	Standardized Estimates (95% Credibility Interval)	
COVID-19 trend (depressed)	-	0.564 (0.052, 0.892)
Means or Intercepts,		
Lonely	2.967 (1.476, 4.825)	3.466 (1.845, 5.721)
Depressed	9.083 (5.028, 13.898)	9.839 (5.632, 14.490)
Lonely→Lonely	28.249 (23.101, 31.262)	27.958 (22.045, 31.092)
Depressed→Depressed	28.702 (24.008, 31.517)	28.518 (23.656, 31.376)
Lonely→Depressed	0.862 (0.425, 1.367)	0.881 (0.321, 1.665)
Depressed→Lonely	0.796 (0.399, 1.196)	0.671 (0.084, 1.269)
Time trend (loneliness)	-0.288 (-0.404, -0.176)	-0.348 (-0.473, -0.225)
Time trend (depressed)	0.175 (0.058, 0.292)	0.170 (0.043, 0.295)
COVID-19 trend (loneliness)	1.597 (0.934, 3.427)	1.160 (0.730, 1.841)
COVID-19 trend (depressed)	0.385 (0.102, 0.726)	0.283 (0.050, 0.557)
Log Residual Variance (Loneliness)	-2.801 (-3.041, -2.570)	-2.804 (-3.050, -2.566)
Log Residual Variance (Depressed)	-2.838 (-3.076, -2.621)	-2.895 (-3.151, -2.670)
Unexplained Variance,		
Lonely	0.998 (0.214, 1.000)	1.000 (0.679, 1.000)
Depressed	1.000 (1.000, 1.000)	1.000 (1.000, 1.000)
Lonely→Lonely	0.975 (0.413, 1.000)	0.989 (0.336, 1.000)
Depressed→Depressed	0.955 (0.411, 1.000)	0.985 (0.031, 1.000)
Lonely→Depressed	0.933 (0.371, 1.000)	0.918 (0.350, 1.000)
Depressed→Lonely	0.972 (0.508, 1.000)	0.923 (0.437, 1.000)

Note. -: a path or parameter not included in the analysis model, hence no estimates.

Table S4.2

Standardized Estimates in Model 2: Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences

Path	**Pre-registered Analysis n = 181**	**Exploratory Analysis (Sex Differences) $n_{boys} = 72$, $n_{girls} = 109$**
$\varphi_{LD} \rightarrow \Delta L$	-0.284 (-0.520, -0.014)	-0.381 (-0.712, 0.183)
$\varphi_{DL} \rightarrow \Delta L$	0.089 (-0.192, 0.352)	-0.175 (-0.546, 0.283)
$\varphi_{LD} \rightarrow \Delta D$	0.178 (-0.045, 0.385)	0.182 (-0.370, 0.593)
$\varphi_{DL} \rightarrow \Delta D$	0.152 (-0.069, 0.351)	-0.145 (-0.511, 0.398)
Female specific effects		
$\varphi_{LD} \rightarrow \Delta L$	-	0.196 (-0.315, 0.528)
$\varphi_{DL} \rightarrow \Delta L$	-	0.287 (-0.182, 0.629)
$\varphi_{LD} \rightarrow \Delta D$	-	0.032 (-0.370, 0.514)

Table S4.2

Standardized Estimates in Model 2: Pre-registered Analysis and Exploratory Analysis on Potential Sex Differences (*continued*)

Path	Pre-registered Analysis n = 181	Exploratory Analysis (Sex Differences) n_{boys} = 72, n_{girls} = 109
$\varphi_{DL} \rightarrow \Delta D$	-	0.339 (-0.198, 0.653)
Female $\rightarrow \Delta L$	-	-0.231 (-0.529, 0.125)
Female $\rightarrow \Delta D$	-	-0.256 (-0.563, 0.098)
$L_5 \rightarrow \Delta L$	-0.261 (-0.466, -0.040)	-0.065 (-0.345, 0.202)
$D_5 \rightarrow \Delta L$	0.157 (-0.032, 0.336)	0.005 (-0.255, 0.267)
$L_5 \rightarrow \Delta D$	0.129 (-0.088, 0.331)	0.084 (-0.185, 0.356)
$D_5 \rightarrow \Delta D$	-0.393 (-0.558, -0.212)	-0.274 (-0.551, -0.020)
$\Delta L \rightarrow L_6$	0.859 (0.747, 0.995)	0.871 (0.674, 1.075)
$\Delta D \rightarrow D_6$	0.794 (0.683, 0.926)	0.888 (0.698, 1.085)
$L_5 \rightarrow L_6$	0.442 (0.251, 0.598)	0.511 (0.223, 0.710)
$D_5 \rightarrow D_6$	0.328 (0.166, 0.474)	0.416 (0.155, 0.623)
Covariance (ΔD & ΔL)	0.859 (0.747, 0.995)	0.871 (0.674, 1.075)
Covariance (L_5 & D_5)	0.794 (0.683, 0.926)	0.888 (0.698, 1.085)
φ_{LD} covary with		
φ_{DL}	0.024 (-0.212, 0.252)	0.039 (-0.185, 0.259)
L_5	0.388 (0.139, 0.576)	0.324 (0.054, 0.541)
D_5	0.009 (-0.225, 0.231)	0.055 (-0.226, 0.328)
φ_{DL} covary with		
L_5	0.097 (-0.194, 0.369)	0.121 (-0.171, 0.385)
D_5	0.225 (-0.047, 0.447)	0.225 (-0.068, 0.480)
Means or Intercepts of		
L_5	1.134 (0.919, 1.346)	1.138 (0.790, 1.498)
D_5	1.591 (1.339, 1.842)	1.454 (1.053, 1.862)
φ_{LD}	0.564 (0.344, 0.789)	0.591 (0.360, 0.826)
φ_{DL}	0.956 (0.698, 1.227)	0.956 (0.694, 1.223)
ΔL	0.101 (-0.242, 0.446)	0.350 (-0.251, 0.796)
ΔD	0.198 (-0.182, 0.572)	0.431 (-0.106, 0.917)
Residual Variance		
ΔL	0.752 (0.591, 0.889)	0.544 (0.230, 0.872)
ΔD	0.788 (0.638, 0.909)	0.581 (0.264, 0.859)

Note. -: a path not included in the analysis model, hence no estimates.

4.2. Inspecting the Stability of Parameter Estimates

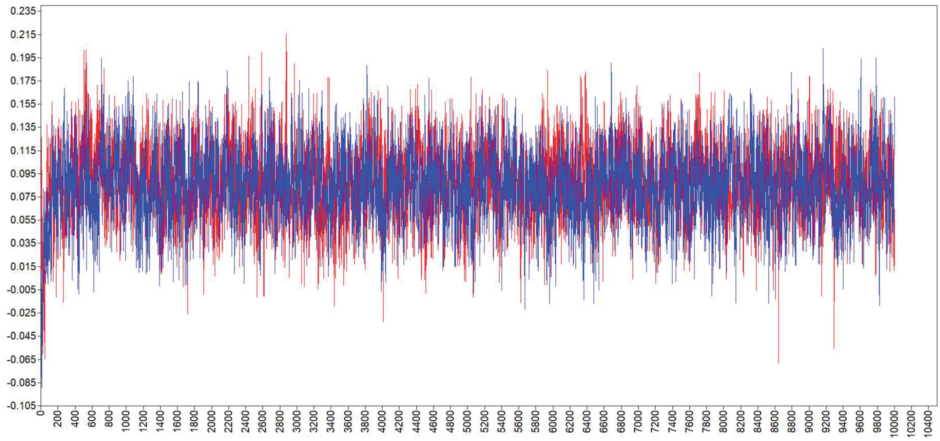
After confirming model convergence by doubling the number of iterations, we additionally inspected the trace plots and density plots of the key parameters to ensure the stability of their estimates. In the trace plots of the half-yearly temporal relations (Figure S4.2.2.1), initial estimates were high, but they quickly stabilized around the final estimate values for the rest of the iterations. In Mplus, the first half of each estimation chain is discarded as burn-in (see https://www.statmodel.com/HTML_UG/chapter16V8.htm). Accordingly, the early fluctuations were not included in the estimation of the parameters central to our hypotheses. As an additional robustness check, we further doubled the number of iterations of the half-yearly model to 25,600. The trace plots from iterations 12,800 to 25,600 showed well-overlapping chains, providing further evidence of stable estimation. This indicated stability in the final estimates as there were no further change trends. All other trace plots we examined showed that chains mixed well with no trends upon increasing number of iterations. All density plots were smooth and unimodal. Overall, they indicated estimates of the parameters were stable.

4.2.1 Hourly Temporal Relations in Model 1a

Figure S4.2.1.1

Trace Plots of Hourly Temporal Relations

Lonely→Depressed



Depressed→Lonely

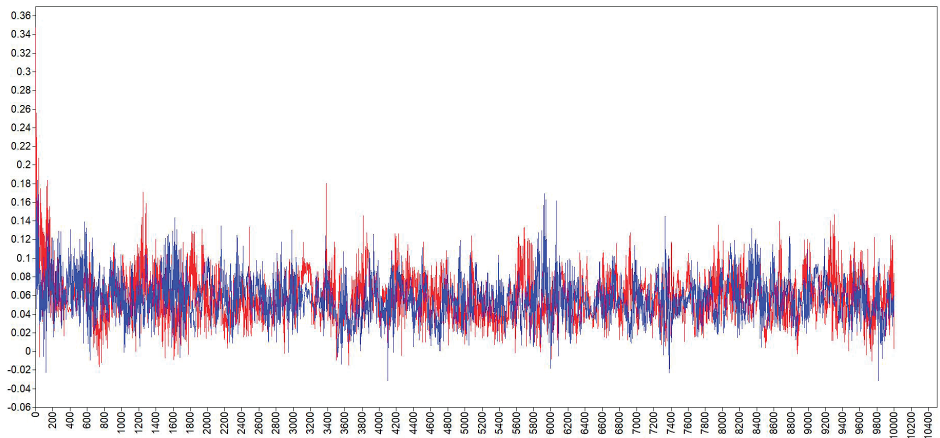
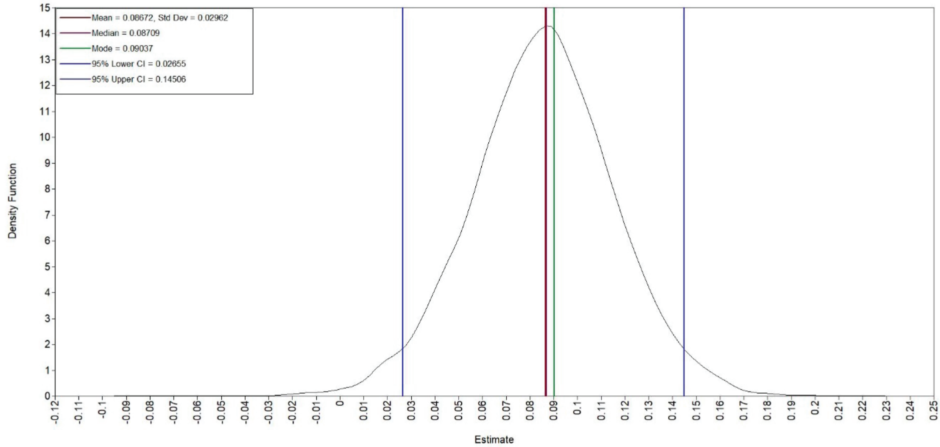


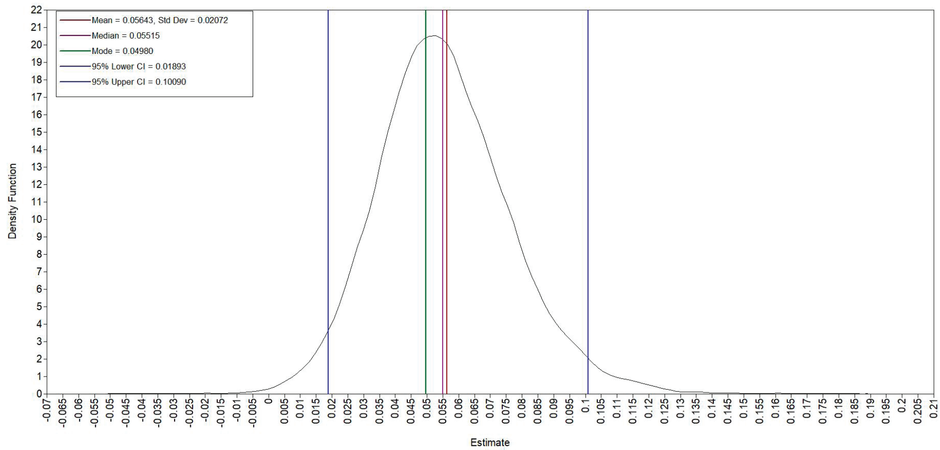
Figure S4.2.1.2

Density Plots of Hourly Temporal Relations

Lonely→Depressed



Depressed→Lonely

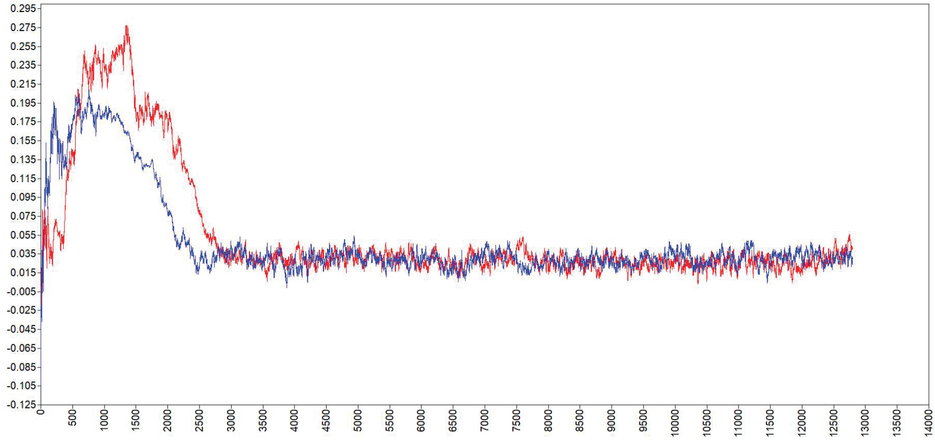


4.2.2 Half-yearly Temporal Relations in Model 1b

Figure S4.2.2.1

Trace Plots of Half-Yearly Temporal Relations

Lonely→Depressed



Depressed→Lonely

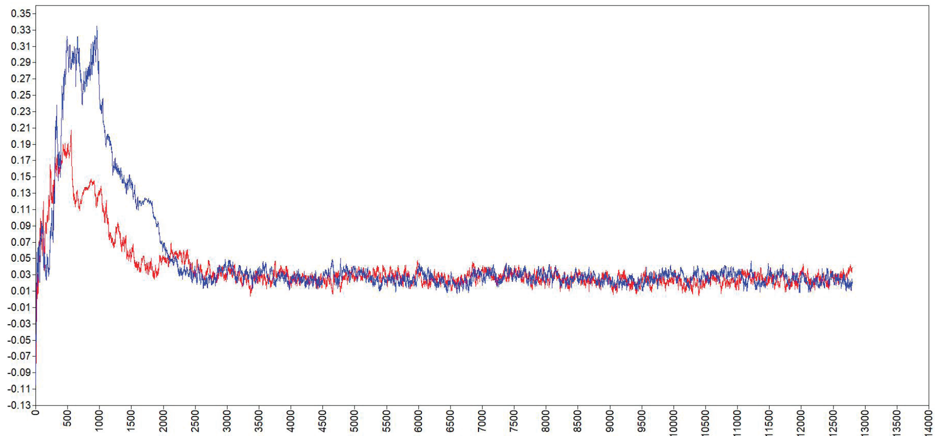
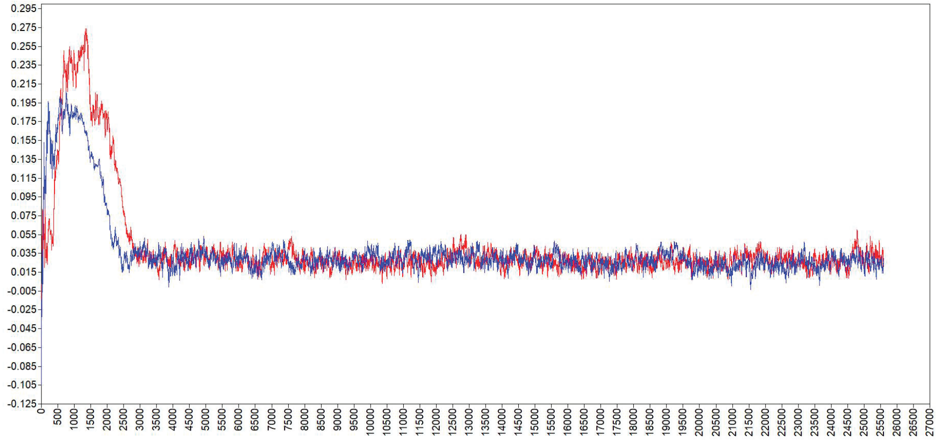


Figure S4.2.2.2

Trace Plots of Half-Yearly Temporal Relations (25600 iterations)

Lonely→Depressed



Depressed→Lonely

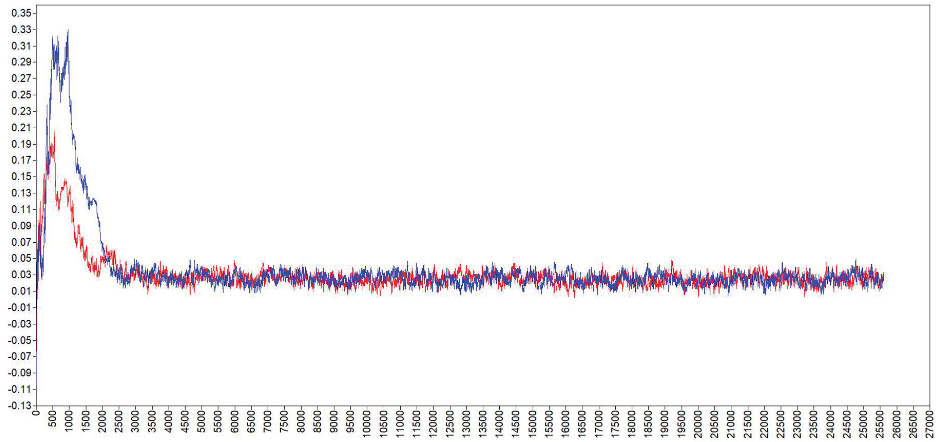
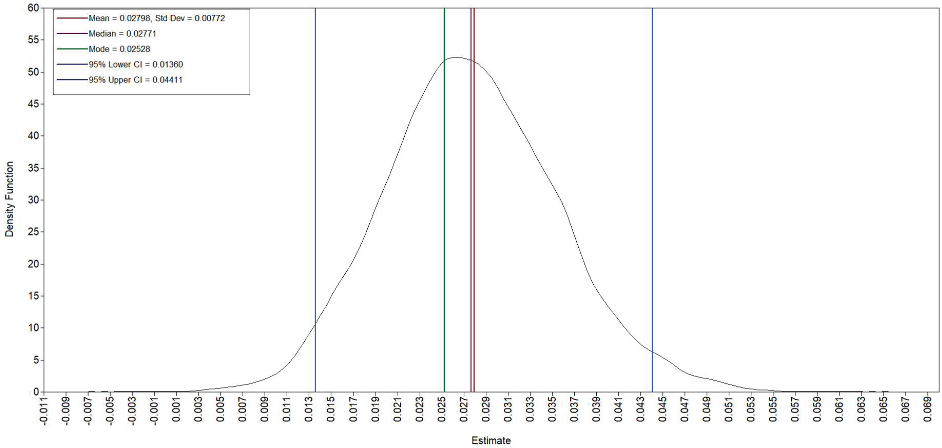


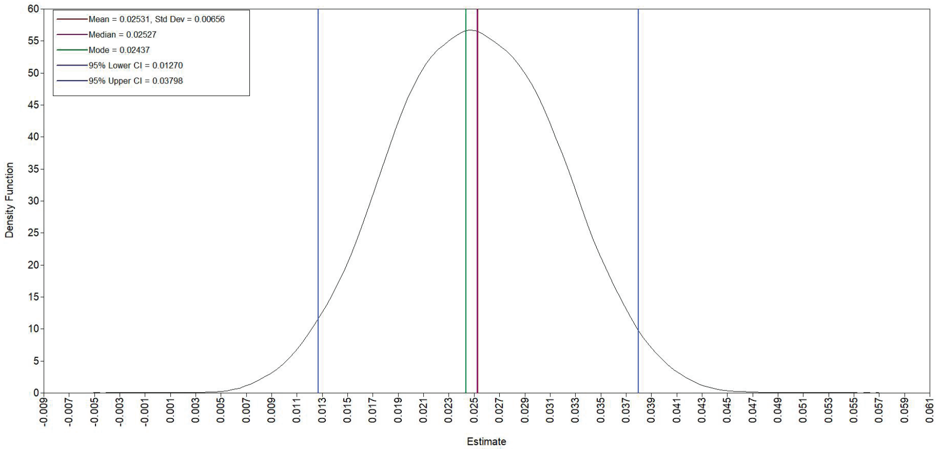
Figure S4.2.2.3

Density Plots of Half-Yearly Temporal Relations

Lonely→Depressed



Depressed→Lonely



4.2.3 Across-time-scale Influence in Model 2

Figure S4.2.3.1

Trace Plots of the Across-time-scale Influence From Hourly Lonely→Depressed Temporal Relation to Half-Yearly Changes in Loneliness

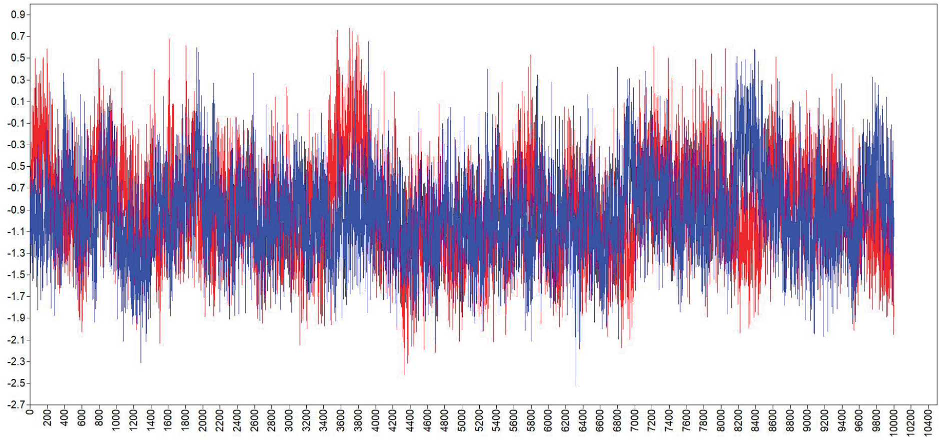
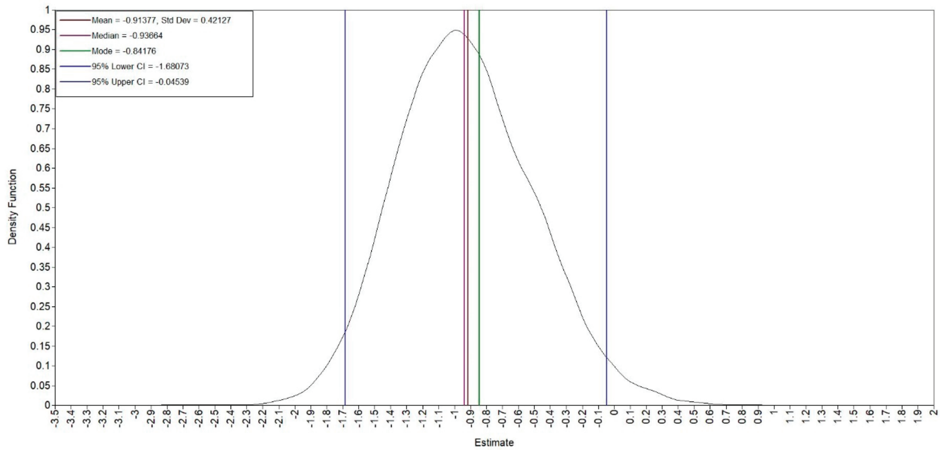


Figure S4.2.3.2

Density Plot of the Across-time-scale Influence From Hourly Lonely→Depressed Temporal Relation to Half-Yearly Changes in Loneliness



SUPPLEMENTAL MATERIAL 5: SENSITIVITY ANALYSIS FOR HYPOTHESIS 2

5.1. One-Step Model to Test Hypothesis 1a and Hypothesis 2 Altogether

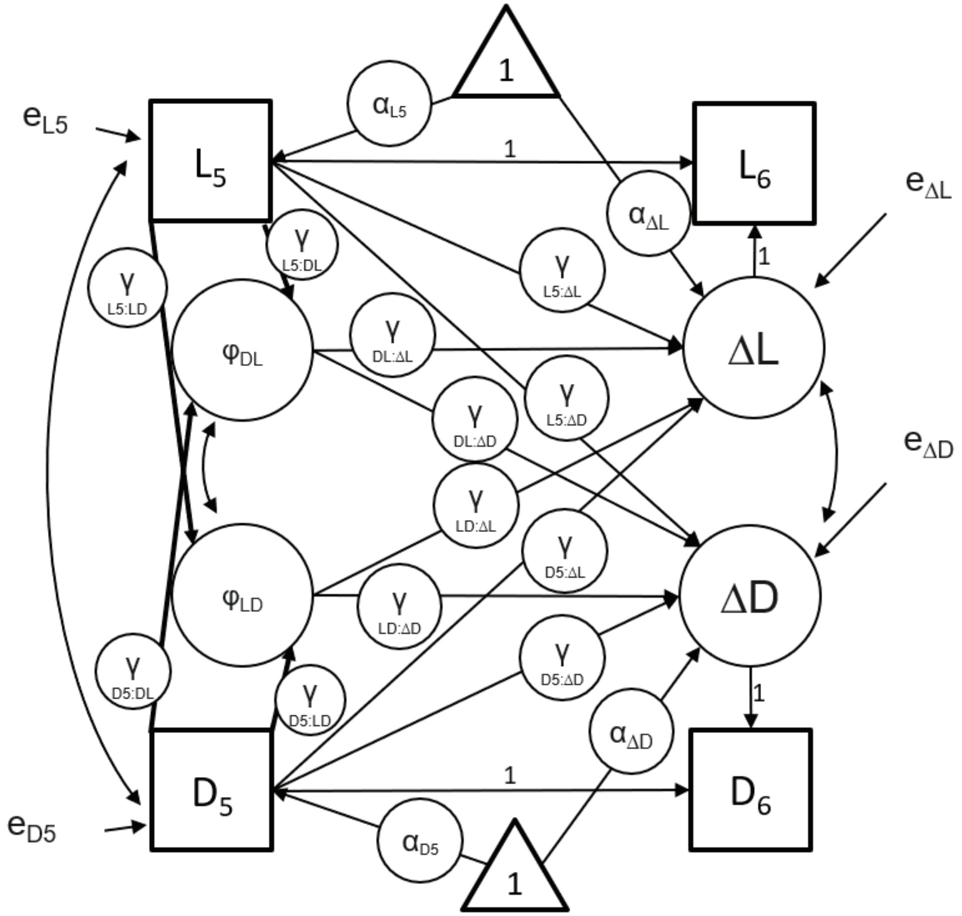
In our pre-registration, we test Hypothesis 1a and Hypothesis 2 separately in Model 1a and Model 2. Technically, it is possible to embed the latent change score model specification from Model 2 directly in the between-person level of Model 1a (R)DSEM so that Hypothesis 1a and Hypothesis 2 are tested together in a one-step approach (Hamaker et al., 2018). We ran a sensitivity analysis with this one-step approach. However, the one-step model did not converge. This nonconvergence is not surprising because our specification was more complex while supported by less data: we modeled two between-person outcomes with an average of 42 repeated measurements per participant (n=84), whereas the published one-step example (Hamaker et al., 2018) used a single between-person outcome with roughly 100 repeated measurements per participant (N=101).

5.2. Additional Regression Paths From Wave 5 Measurements to ESM Estimates

The ESM study occurred not at W5, but three months after W5 and three months before W6. Therefore, analytically, it was possible to specify additional regression paths in Model 2 in which person-specific ESM estimates of hourly loneliness and depressed feelings were temporally predicted by W5 measurements of loneliness and depressive symptoms. Accordingly, we conducted a sensitivity analysis that added these additional paths to the H2 model (paths in bold, Figure S5.2). The results for H2 were unchanged, as the values of the key estimates that tested H2 were very close to the estimates in the preregistered model and are similarly (non)significant (Table S5.2). The standardized residual variance of ESM estimates are .829 and .924 for φ_{LD} and φ_{DL} respectively. These variances indicate the proportion of unexplained variance between adolescents. In other words, in this sensitivity analysis, W5 loneliness and depressive symptoms could only account for less than 20% of the variance of the ESM estimates. This means that that person-specific hourly relations were mostly explained by factors other than W5 loneliness and depressive symptoms.

Figure S5.2

Full Specifications of Model 2 (Across-Timescale Effects) Sensitivity Analysis.



Note. D: Depressive Symptoms; L: Loneliness; ΔD: Latent change in Depressive Symptoms; ΔL Latent change in Loneliness; e: Residual; α: mean/intercept; φ: person-specific estimates of within-person temporal relations extracted from Model 1a; γ: path estimate (":" denotes an effect, e.g., $\gamma_{D5:\Delta D}$ denotes the path estimate of the effect from D_5 to ΔD); Subscript 5, 6: Measured at Wave 5 or Wave 6. This model is built on the pre-registered Model 2 (Figure S3.1.2). The changes in this sensitivity analysis model are that Wave 5 measurements of loneliness and depressive symptoms predict person-specific ESM estimates, as denoted by bold arrows.

Table S5.2

Standardized Estimates in Model 2: Sensitivity Analysis on Modeling the Temporal Relations From Wave 5 Measurements to ESM Person-Specific Estimates

Path	Sensitivity Analysis n = 181
$\varphi_{LD} \rightarrow \Delta L$	-0.302 (-0.524, -0.048)
$\varphi_{DL} \rightarrow \Delta L$	0.050 (-0.219, 0.333)
$\varphi_{LD} \rightarrow \Delta D$	0.163 (-0.061, 0.369)
$\varphi_{DL} \rightarrow \Delta D$	0.140 (-0.089, 0.362)
$L_5 \rightarrow \Delta L$	-0.249 (-0.456, -0.023)
$D_5 \rightarrow \Delta L$	0.162 (-0.023, 0.345)
$L_5 \rightarrow \Delta D$	0.128 (-0.078, 0.331)
$D_5 \rightarrow \Delta D$	-0.380 (-0.557, -0.183)
$L_5 \rightarrow \varphi_{LD}$	0.422 (0.158, 0.628)
$D_5 \rightarrow \varphi_{LD}$	-0.151 (-0.367, 0.099)
$L_5 \rightarrow \varphi_{LD}$	0.072 (-0.220, 0.361)
$D_5 \rightarrow \varphi_{DL}$	0.199 (-0.075, 0.441)
$\Delta L \rightarrow L_6$	0.858 (0.745, 0.988)
$\Delta D \rightarrow D_6$	0.788 (0.673, 0.924)
$L_5 \rightarrow L_6$	0.831 (0.720, 0.956)
$D_5 \rightarrow D_6$	0.900 (0.784, 1.033)
Covariance (ΔD & ΔL)	0.444 (0.259, 0.601)
Covariance (L_5 & D_5)	0.335 (0.185, 0.473)
Covariance (φ_{LD} & φ_{DL})	-0.002 (-0.231, 0.232)
Means or Intercepts of	
L_5	1.151 (0.941, 1.362)
D_5	1.597 (1.324, 1.853)
ΔL	0.103 (-0.286, 0.436)
ΔD	0.215 (-0.147, 0.586)
Residual Variance	
ΔL	0.750 (0.586, 0.889)
ΔD	0.800 (0.647, 0.920)
φ_{LD}	0.829 (0.640, 0.964)
φ_{DL}	0.924 (0.774, 0.996)

5.3. Excluding an Outlier in ESM Person-Specific Estimates

Our preregistration specified that exclusions would be limited to potential careless responding, indicated by very short response times or invariant responding across items that included reverse-coded items. Nevertheless, we noticed one participant has a very high ESM person-specific estimate for the hourly relation from feeling lonely to feeling depressed (see Figure 5.2 in main text). However, this participant did not appear to provide problematic data: they completed 80% of ESM assessments and showed within-person variation in both loneliness and depressed feelings, meaning they would not qualify for exclusion under our preregistered criteria. We therefore retained this case in the main analyses. Still, in the interest of transparency and robustness, we also ran a sensitivity analysis excluding this participant. The overall pattern of results remained unchanged in terms of the directions of the key path estimates (Table S5.3).

One path, however, became significant: person-specific estimates for the hourly association from feeling lonely to feeling depressed significantly predicted half yearly increases in depressive symptoms. This suggests that although adolescents who showed stronger hourly increases in depressed feelings following heightened loneliness appeared protected against half yearly increases in loneliness, they may also have been at greater risk for increases in depressive symptoms over the same period. However, this finding should be interpreted with caution. Because it emerged only after excluding an outlying case, it may reflect an inflated risk of a Type I error (i.e., false positives) rather than a stable effect in our parametric analysis (André, 2022; M. Bakker & Wicherts, 2014). Further research is needed before drawing substantive conclusions from this result.

In the main text, we report and interpret the preregistered analyses. Future studies with larger samples are needed to determine whether this additional significant association is replicable or instead reflects an unstable result that emerged after departing from the preregistered plan.

Table S5.3

Key Standardized Estimates in Model 2: Sensitivity Analysis of Excluding an Outlier

Path	**Sensitivity Analysis (n = 180)**
$\varphi_{LD} \rightarrow \Delta L$	-0.299 (-0.533, -0.031)
$\varphi_{DL} \rightarrow \Delta L$	0.086 (-0.171, 0.354)
$\varphi_{LD} \rightarrow \Delta D$	0.271 (0.050, 0.466)
$\varphi_{DL} \rightarrow \Delta D$	0.125 (-0.087, 0.328)

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RESEARCH DATA MANAGEMENT AND PRIVACY

The research in this dissertation was conducted in compliance with the General Data Protection Regulation (GDPR) and all applicable laws and ethical guidelines. All analyses in this dissertation were secondary data analyses, i.e., analyzing existing data without collecting new data. The seven datasets analyzed for this dissertation belong to existing projects that have been approved by respective ethical committees from Radboud University and other institutes (ethics approval protocol numbers: ECSW20170805-516, ECSW-2020-122, ECSW-2020-182, ECSW-2021-043, ML7321, ML8514, EC-2017.95, and BC-09559).

Regarding the studies from the G(F)ood together project led by Radboud University used in Chapter 3 and 5, the privacy of participants has been warranted using random individual participant IDs. Encrypted pseudonymization key files linking these random participant IDs with identifiable personal information were stored on a secure network drive and were only accessible to the principal investigators. The key files were destroyed within one month after data processing was completed.

Radboud University and the Behavioural Science Institute (BSI) have set strict conditions for the management of research data. Research Data Management was conducted according to the FAIR principles. All research data resulting from this dissertation were handled in accordance with the university's research data management policy (https://www.ru.nl/rdm/) and the BSI's research data management protocol (https://www.radboudnet.nl/bsi/rdm). To enhance open science and transparent research practices, all publication packages associated with the publications in this dissertation were registered in the Research Information Services (RIS) system of Radboud University and deposited on the Open Science Framework (https://osf.io) or in the Radboud Data Repository (https://data.ru.nl). Research data containing potentially identifiable personal information used from the G(F)ood together project are excluded from their respective publication packages.

Table RDM

Overview of the publication packages in this dissertation

Chapter	DOI
Chapter 2: A Theory-Informed Emotion Regulation Variability Index: Bray–Curtis Dissimilarity	https://doi.org/10.17605/OSF.IO/VZH2N
Chapter 3: Emotion Differentiation in Adolescents: Short-term Trade-offs with Regulation Variability and Emotion Intensity	https://doi.org/10.17605/OSF.IO/CQ6N4
Chapter 4: Negative Emotion Transitions May Have Immediate Benefits in Decreasing Negative Emotions in Daily Life.	https://doi.org/10.17605/OSF.IO/E6U97
Chapter 5: Loneliness and Depressive Symptoms in Adolescents: A Multi-Timescale Examination	https://doi.org/10.17605/OSF.IO/RJAQ4

ENGLISH SUMMARY

Emotions are dynamic. We rarely experience the exact same emotions as the hours pass. Emotions inform us of the situations we are in, signal our needs, and prepare us for responding. Emotions change as situations evolve and as we influence emotions through what is known as emotion regulation.

The everyday dynamics of emotions and emotion regulation in adolescents and young adults – hereafter referred to as young people – are important. Young people's negative emotions such as anger, sadness, and anxiety can be intense at times and can fluctuate rigorously in daily lives (Bailen et al., 2019; Reitsema et al., 2022; Zimmermann & Iwanski, 2014). These dynamics in negative emotions are common when young people face academic, social, and vocational transitions in adolescence and young adulthood, periods where puberty and brain maturation take place. Young people gradually learn to regulate negative emotions on their own without relying on adult caretakers. If young people ineffectively regulate negative emotions, however, they are prone to poor social health (e.g., loneliness) and mental health (e.g., psychopathology such as depression and anxiety). Therefore, the dynamics of emotions and the associated emotion regulation in young people's daily lives not only reflect how they react to situations and respond to emotions in the short term, but may shape their long-term social and mental health.

Knowing what one feels (i.e. emotion differentiation) is theorized to help young people regulate their emotions. When young people can make sense of what they feel, they are informed by their emotions to choose the right type of emotion regulation for the situation (Aldao et al., 2015; Kashdan et al., 2015). Emotion differentiation involves gaining clarity in which emotions they feel and how strongly they feel, i.e., the type and intensity of emotions (Barrett et al., 2001; Erbas et al., 2021; Gross & Jazaieri, 2014). The type of emotions informs what young people experience qualitatively (e.g., "I feel bored reading on.") and prepares them to respond in an emotion-specific manner (Frijda, 2016). The intensity of emotions is a yardstick for significance, informing young people how much they care about a situation and whether they should respond by influencing the situation or the emotions (Frijda, 2016; Greenberg, 2006; Schwarz & Clore, 1983). In parallel, emotion regulation also varies in type and intensity. The type of emotion regulation refers to the deployed strategy of emotion regulation, such as reappraisal (e.g., "It may get better soon. Let's read on.") or distraction (e.g., "Let's watch Netflix for a while before reading on"), which differ in proposed mechanisms and their effects in influencing emotions (Aldao et al., 2010). The intensity in emotion regulation refers to how strongly someone engages with a certain strategy (Blanke et al., 2022).

Empirically, little is known about how emotion differentiation of young people is followed by the changes in the type and intensity of emotion regulation. Furthermore, empirical studies about emotions and emotion regulation in daily life have mostly focused on how their intensity changes, even though dynamics of emotion and emotion regulation must be considered in both intensity and type. If dynamics of emotion and emotion regulation were like piano music, current research can be described as focusing only on the loudness (intensity) but not on which keys (types) on a piano are played. Without considering changes in types, there is no melody, and the dynamics in emotion and emotion regulation are incomplete.

Therefore, this dissertation aims to examine young people's emotion (regulation) dynamics with a specific focus on type-related dynamics . To do so, four type-related dynamics in emotional processes are studied: emotion regulation variability (i.e., how young people change their strategies in regulating negative emotions; Chapters 2 and 3), emotion differentiation (i.e., how well young people distinctively label their emotional experience; Chapter 3), negative emotion transitions (i.e., the change from experiencing one negative emotion to another across time), and temporal coupling between loneliness and depressive symptoms (i.e., how likely young people feel more lonely after feeling depressed, and vice versa; Chapter 5). In these four empirical chapters (Chapters 2 to 5), I analyzed seven existing datasets. Six of the seven datasets contained hour-to-hour data on experienced emotion and emotion regulation self-reported by 848 young people in their daily lives (total number of observations = 42878, average age = 18, age range = 11 to 30, 59% female). These temporally granular data allowed me to investigate short-term emotion (regulation) dynamics in young people's daily lives. In the seventh dataset, 777 young people reported five times from 2017 to 2021 on their social and mental health (number of observations = 1880, average age at first assessment = 13, 53% female). One of the six hourly datasets assessed a subset of adolescents from the seventh long-term dataset, allowing me to investigate how short-term dynamics in emotions shape long-term changes in social and mental health.

In Chapter 2, I translated a methodological approach from ecology, Bray-Curtis dissimilarity (Baselga, 2013b) to emotion research to quantify changes from one emotion (regulation) type to another. Through simulation studies, I demonstrated that Bray-Curtis dissimilarity reliably measures the two theorized processes about how emotion regulation changes (i.e., emotion regulation variability): switching between emotion regulation strategies (e.g., from distracting oneself to reappraising) and overall intensity changes in emotion regulation (e.g., initiation or inhibition) (Aldao et al., 2015). Applying Bray-Curtis dissimilarity to three real-world datasets, I found that greater switching between emotion regulation strategies is robustly related to subsequently lower levels of negative emotion intensity within young adults. This indicated that switching between emotion regulation strategies may be beneficial in attaining a low intensity of negative emotions.

In Chapter 3, I tested the theorized effect of emotion differentiation on emotion regulation variability and subsequent changes in emotion intensity. I broke down the effects on emotion regulation as its variability (i.e., how regulation strategies change; calculated by Bray-Curtis dissimilarity) and its outcome (i.e., subsequent emotion intensity). I found that emotion differentiation and emotion regulation variability hindered each other. Moments where young people know better about what they feel are followed by more stable emotion regulation strategy use (lower emotion regulation variability). In reverse, after young people change their emotion regulation strategy use, they know their emotions less well at the next moment. Furthermore, emotion differentiation and emotion regulation variability may together shape subsequent emotion intensity outcomes. Controlling for emotion regulation intensity, both heightened differentiation and regulation variability preceded emotionally feeling worse, which referred to increased negative emotions and decreased positive emotions. However, these analyses might not be directly translated to guide behavioural changes due to model complexity. Still, these results suggest that there can be discomfort, in terms of feeling worse emotionally, after heightened emotion differentiation or emotion regulation variability.

In Chapter 4, I extended the exploration of type-related emotion dynamics from emotion differentiation, that occur within a single moment, to emotion transitions, that happen across moments. Emotion transitions describe how emotions change from one type to another over time. Even if a transition is between negative emotions (e.g., from anger to sadness), it may support emotion regulation by enhancing clarity and action readiness, compared to staying stuck in one emotion (Hollenstein et al., 2013; Singh et al., 2021). I applied Bray-Curtis dissimilarity to negative emotions to measure transitions between negative emotions. I found that, within the same hourly interval, negative emotion transitions were significantly associated with reductions in overall negative emotion intensity. Moreover, such reductions were larger among young adults with higher depressive symptoms. This indicated that negative emotion transitions may be closely related to decreasing intensity of negative emotions, especially for young adults with depressive symptoms.

These chapters (Chapter 2 to 4) explored short-term emotion outcomes subsequent to different emotion (regulation) dynamics, but emotion dynamics may also shape long-term changes in social and mental health. Loneliness and depressed symptoms are theorized to influence each other at both short- and long-term timescales (Cacioppo & Cacioppo, 2018), but evidence on multiple timescales is scarce. I found that there is a reinforcing feedback loop between loneliness and depressed symptoms, both short-term (1.5-hourly) and long-term (half-yearly). In other words, once loneliness or depressive symptoms were heightened, the other tended to increase in turn after 1.5 hours or half a year. Additionally, I found that short-term dynamics between loneliness and depressed feelings might shape long-term changes in loneliness: Adolescents who felt more depressed 1.5 hours after heightened loneliness showed smaller half-yearly increases in trait loneliness. However, this buffering effect was not predicted by the hourly depressed-to-loneliness relation, nor did either hourly relation predict half-yearly changes in depressive symptoms. In sum, findings in Chapter 5 suggest that feeling depressed shortly after loneliness can be a normative process that protects adolescents from having long-term loneliness.

All empirical chapters showed that type-related dynamics in emotion and emotion regulation can precede or accompany short-term emotion outcomes (Chapter 2, 3, 4, 5) and long-term outcomes in social health, whereas associations with long-term mental health outcomes were not observed (Chapter 5). Importantly, these type-related dynamics predicted the outcomes above and beyond the intensity of emotion and emotion regulation (Chapter 3, 4, 5), indicating we can better predict short-term and long-term outcomes by considering emotion (regulation) dynamics in type in addition to intensity. Taken together, type-related dynamics is crucial to describe how young people adapt to everyday emotional experiences. The studies in this dissertation are starting steps toward understanding type-related emotion (regulation) dynamics. Future research should clarify how these dynamics change across age and developmental phases, include positive emotions beyond negative emotions, advance methodology to quantify type-related dynamics, and investigate how to stimulate type-related changes in emotions and emotion regulation in daily life.

Although further research is warranted, an awareness of type-related dynamics can already inform us about how we might respond to young people's negative emotional experiences differently. In moments when young people struggle with regulating their emotions, instead of saying, "Let's try harder", we might ask, "Is there another way to engage with these emotions?" Rather than focusing only on reducing the intensity of negative emotions, we might ask, "Are there other emotions to arrive at?" Much like music is defined not just by loudness but also by the dynamics between playing different keys, we must understand our emotion and emotion regulation beyond their intensity but how the type-related dynamics between emotions and between the ways we regulate them. Attuning to type-related emotion dynamics may be key to understanding, and eventually guiding, the melodies of our emotional lives.

DUTCH SUMMARY (NEDERLANDSE SAMENVATTING)

Emoties zijn dynamisch. Gedurende de dag ervaren we zelden steeds precies dezelfde emoties. Emoties vertellen ons iets over de situatie waarin we zitten, maken duidelijk wat we nodig hebben en bereiden ons voor om te reageren. Emoties veranderen naarmate situaties zich ontwikkelen en doordat we emoties beïnvloeden via wat bekend staat als emotieregulatie.

De alledaagse dynamiek van emoties en emotieregulatie bij adolescenten en jongvolwassenen – hierna aangeduid als jongeren – is van groot belang. Negatieve emoties van jongeren, zoals boosheid, verdriet en angst, kunnen soms intens zijn en in het dagelijks leven sterk wisselen (Bailen et al., 2019; Reitsema et al., 2022; Zimmermann & Iwanski, 2014). Deze dynamiek in negatieve emoties komt vaak voor wanneer er veranderingen in school of opleiding, in het werk of sociaal gezien plaatsvinden tijdens de adolescentie en jongvolwassenheid, perioden waarin de puberteit en rijping van de hersenen plaatsvinden. Jongeren leren gaandeweg om negatieve emoties zelfstandig te reguleren, zonder daarbij te steunen op ouders of andere verzorgers. Als jongeren negatieve emoties echter niet effectief reguleren, lopen zij een groter risico op een slechtere sociale gezondheid (bijvoorbeeld eenzaamheid) en mentale gezondheid (bijvoorbeeld psychopathologie, zoals depressie en angst). De dynamiek van emoties en de bijbehorende emotieregulatie in het dagelijks leven van jongeren weerspiegelen daarom niet alleen hoe zij op korte termijn op situaties en emoties reageren, maar kunnen ook hun sociale en mentale gezondheid op de lange termijn beïnvloeden.

Weten wat je voelt (ofwel: emotionele differentiatie) zou jongeren volgens theorieën helpen om hun emoties te reguleren. Wanneer jongeren betekenis kunnen geven aan wat zij voelen, bieden emoties informatie over welke vorm van emotieregulatie in die situatie passend is (Aldao et al., 2015; Kashdan et al., 2015). Emotionele differentiatie gaat over het verkrijgen van meer duidelijkheid over welke emoties iemand voelt en hoe sterk die emoties zijn, oftewel: het type en de intensiteit van emoties (Barrett et al., 2001; Erbas et al., 2021; Gross & Jazaieri, 2014). Het type emotie zegt iets over wat jongeren kwalitatief ervaren (bijvoorbeeld: "Ik voel me verveeld terwijl ik doorlees") en bereidt hen voor om op een emotiespecifieke manier te reageren (Frijda, 2016). De intensiteit van emoties is een graadmeter voor het belang van een situatie: die laat jongeren zien hoeveel een situatie voor hen betekent en of zij het best kunnen reageren door de situatie ofwel hun emoties te beïnvloeden (Frijda, 2016; Greenberg, 2006; Schwarz & Clore, 1983). Ook emotieregulatie verschilt in type en intensiteit. Het type emotieregulatie verwijst naar de strategie die iemand inzet, zoals cognitieve herwaardering (bijvoorbeeld: "Misschien wordt het zo beter. Ik ga verder lezen") of afleiding (bijvoorbeeld: "Ik ga eerst even Netflix kijken voordat ik verder lees"), die verschillen in de veronderstelde mechanismen en in de manier waarop zij emoties beïnvloeden (Aldao et al., 2010). De intensiteit van emotieregulatie verwijst naar hoe sterk iemand een bepaalde strategie inzet (Blanke et al., 2022).

Empirisch is er nog weinig bekend over hoe emotionele differentiatie bij jongeren wordt gevolgd door veranderingen in het type en de intensiteit van emotieregulatie. Bovendien hebben empirische studies naar emoties en emotieregulatie in het dagelijks leven zich meestal alleen gericht op veranderingen in intensiteit, terwijl de dynamiek van emoties en emotieregulatie juist zowel in termen van intensiteit als van type moet worden bekeken. Als we de dynamiek van emotie en emotieregulatie vergelijken met pianomuziek, dan richt eerder onderzoek zich vooral op het volume (intensiteit), maar niet op welke toetsen (types) op de piano worden aangeslagen. Zonder veranderingen in type is er geen melodie te horen, en blijft de dynamiek van emoties en emotieregulatie onvolledig.

Daarom is het doel van dit proefschrift om de dynamiek van emoties en emotieregulatie bij jongeren te onderzoeken, met specifieke aandacht voor type-specifieke dynamiek. Daarvoor worden vier type-specifieke dynamieken in emotionele processen bestudeerd: variabiliteit in emotieregulatie (dat wil zeggen: hoe jongeren van strategie veranderen bij het reguleren van negatieve emoties; hoofdstukken 2 en 3), emotionele differentiatie (dat wil zeggen: hoe goed jongeren hun emotionele ervaringen onderscheidend kunnen benoemen; hoofdstuk 3), transities tussen negatieve emoties (dat wil zeggen: hoe de ene negatieve emotie in de loop van de tijd overgaat in een andere) en temporele samenhang tussen eenzaamheid en depressieve symptomen (dat wil zeggen: hoe groot de kans is dat jongeren zich eenzamer voelen nadat zij zich somber of depressief hebben gevoeld, en omgekeerd; hoofdstuk 5). In deze vier empirische hoofdstukken (hoofdstukken 2 t/m 5) heb ik zeven bestaande datasets geanalyseerd. Zes van de zeven datasets bevatten gegevens die van uur tot uur zijn verzameld over ervaren emoties en emotieregulatie, die 848 jongeren in hun dagelijks leven zelf rapporteerden (totaal aantal observaties = 42.878, gemiddelde leeftijd = 18 jaar, leeftijdsbereik = 11 tot 30 jaar, 59% vrouw). Deze fijnmazige temporele gegevens maakten het mogelijk om korte-termijn dynamiek in emoties en emotieregulatie in het dagelijks leven van jongeren te onderzoeken. In de zevende dataset rapporteerden 777 jongeren tussen 2017 en 2021 op vijf meetmomenten over hun sociale en mentale gezondheid (aantal observaties = 1.880, gemiddelde leeftijd bij de eerste meting = 13 jaar, 53% vrouw). In één van de zes datasets (van uur tot uur) werd een deel van de adolescenten uit de zevende lange-termijn dataset gevolgd, waardoor ik kon onderzoeken hoe korte-termijn dynamiek in emoties samenhangt met veranderingen in sociale en mentale gezondheid op de lange termijn.

In hoofdstuk 2 heb ik een methodologische benadering uit de ecologie, de Bray-Curtis-dissimilarity (Baselga, 2013b), toegepast in het emotieonderzoek om veranderingen van het ene type emotie(regulatie) naar het andere te kwantificeren. Met behulp van simulatiestudies liet ik zien dat de Bray-Curtis-dissimilarity op betrouwbare wijze de twee veronderstelde processen meet waarmee emotieregulatie verandert (dat wil zeggen: variabiliteit in emotieregulatie): schakelen tussen emotieregulatiestrategieën (bijvoorbeeld van jezelf afleiden naar herwaarderen) en veranderingen in de totale intensiteit van emotieregulatie (bijvoorbeeld initiatie of inhibitie) (Aldao et al., 2015). Door de Bray-Curtis-dissimilarity toe te passen op drie real-world datasets, vond ik dat vaker schakelen tussen emotieregulatiestrategieën consistent samenhing met een daaropvolgende lagere intensiteit van negatieve emoties bij jongvolwassenen. Dit wijst erop dat schakelen tussen emotieregulatiestrategieën gunstig kan bijdragen aan een lage intensiteit van negatieve emoties.

In hoofdstuk 3 heb ik het veronderstelde effect van emotionele differentiatie op variabiliteit in emotieregulatie en daaropvolgende veranderingen in emotionele intensiteit getoetst. Ik heb de effecten op emotieregulatie uitgesplitst naar de variabiliteit ervan (dat wil zeggen: hoe regulatiestrategieën veranderen; berekend met Bray-Curtis dissimilarity) en de uitkomst ervan (dat wil zeggen: de emotionele intensiteit op het daaropvolgende meetmoment). Ik vond dat emotionele differentiatie en variabiliteit in emotieregulatie elkaar leken te bemoeilijken. Momenten waarop jongeren beter weten wat zij voelen, worden gevolgd door stabieler gebruik van emotieregulatiestrategieën (lagere variabiliteit in emotieregulatie). Omgekeerd geldt dat jongeren, nadat zij van emotieregulatiestrategie zijn veranderd, op het volgende moment minder goed weten wat zij voelen. Daarnaast kunnen emotionele differentiatie en variabiliteit in emotieregulatie samen de daaropvolgende intensiteit van emoties beïnvloeden. Gecontroleerd voor de intensiteit van emotieregulatie gingen zowel sterkere emotionele differentiatie als grotere variabiliteit in emotieregulatie vooraf aan een verslechtering van hoe iemand zich emotioneel voelt, wat inhield dat negatieve emoties toenamen en positieve emoties afnamen. Door de complexiteit van het model zijn deze analyses echter niet direct te vertalen naar handvatten voor gedragsverandering. Toch suggereren deze resultaten dat verhoogde emotionele differentiatie of variabiliteit in emotieregulatie gepaard kan gaan met emotioneel ongemak, in de zin van zich emotioneel slechter voelen.

In hoofdstuk 4 heb ik de verkenning van type-specifieke emotiedynamiek verlegd van emotionele differentiatie, dat zich binnen één moment voordoet, naar emotietransities, die zich tussen momenten voordoen. Emotietransities beschrijven hoe emoties in de loop van de tijd van het ene type naar het andere overgaan. Zelfs wanneer zo'n transitie plaatsvindt tussen negatieve emoties (bijvoorbeeld van boosheid naar verdriet), kan die emotieregulatie ondersteunen door, vergeleken met vast blijven zitten in één emotie, meer helderheid en actiebereidheid te bieden (Hollenstein et al., 2013; Singh et al., 2021). Ik heb Bray-Curtis dissimilarity toegepast op negatieve emoties om transities tussen negatieve emoties te meten. Ik vond dat negatieve emotietransities binnen hetzelfde uur significant samenhingen met afnames in de totale intensiteit van negatieve emoties. Bovendien waren zulke afnames groter bij jongvolwassenen met ernstigere depressieve symptomen. Dit wijst erop dat negatieve emotietransities nauw verband kunnen houden met een afname van de intensiteit van negatieve emoties, vooral bij jongvolwassenen met depressieve symptomen.

Deze hoofdstukken (hoofdstuk 2 t/m 4) verkenden korte-termijn uitkomsten in emoties die volgden op verschillende dynamieken van emotie(regulatie), maar emotiedynamiek kan ook invloed hebben op lange-termijn veranderingen in sociale en mentale gezondheid . Er wordt verondersteld dat eenzaamheid en depressieve symptomen elkaar zowel binnen korte als lange tijdschalen beïnvloeden (Cacioppo & Cacioppo, 2018), maar empirisch bewijs voor invloed op meerdere tijdschalen is schaars. Ik vond dat er zowel op de korte termijn (met tussenpozen van 1,5 uur) als op de lange termijn (halfjaarlijks) sprake is van een zelfversterkende feedbacklus tussen eenzaamheid en depressieve symptomen. Met andere woorden: zodra eenzaamheid of depressieve symptomen toenamen, nam het andere op zijn beurt na 1,5 uur of een half jaar toe. Daarnaast vond ik dat korte-termijn dynamiek tussen eenzaamheid en depressieve gevoelens mogelijk lange-termijn veranderingen in eenzaamheid met zich meebrengt: adolescenten die zich 1,5 uur na verhoogde eenzaamheid meer depressief voelden, lieten halfjaarlijks kleinere toenames in trait-eenzaamheid zien. Dit bufferende effect werd echter niet voorspeld door de korte-termijn relatie van depressieve gevoelens naar eenzaamheid, en ook voorspelde geen van beide korte-termijn relaties de halfjaarlijkse veranderingen in depressieve symptomen. Alles bij elkaar wijzen de bevindingen in hoofdstuk 5 erop dat het adaptief kan zijn om zich kort na eenzaamheid depressief te voelen en dat dit adolescenten kan beschermen tegen eenzaamheid op de lange termijn.

Alle empirische hoofdstukken lieten zien dat type-specifieke dynamiek in emoties en emotieregulatie vooraf kan gaan aan korte-termijn uitkomsten in emoties of daarmee gepaard kan gaan (hoofdstuk 2, 3, 4 en 5) en lange-termijn uitkomsten in sociale gezondheid, terwijl er geen verbanden met lange-termijn uitkomsten in mentale gezondheid werden gevonden (hoofdstuk 5). Belangrijk is dat deze type-specifieke dynamieken deze uitkomsten voorspelden boven op de intensiteit van emotie en emotieregulatie (hoofdstuk 3, 4 en 5). Dat wijst erop dat we korte-termijn en lange-termijn uitkomsten beter kunnen voorspellen wanneer we naast intensiteit ook rekening houden met type-specifieke dynamiek in emotie(regulatie). Alles bij elkaar genomen is type-specifieke dynamiek cruciaal om te beschrijven hoe jongeren zich aanpassen aan alledaagse emotionele ervaringen. De studies in dit proefschrift vormen een eerste stap in het begrijpen van type-specifieke dynamiek in emotie(regulatie). Toekomstig onderzoek zou moeten verduidelijken hoe deze dynamieken veranderen met leeftijd of ontwikkelingsfase, zowel positieve als negatieve emoties meenemen, de methodologie voor het kwantificeren van type-specifieke dynamiek verder ontwikkelen, en onderzoeken hoe type-specifieke veranderingen in emoties en emotieregulatie in het dagelijks leven kunnen worden gestimuleerd.

Hoewel verder onderzoek nodig is, kan aandacht voor type-specifieke dynamiek ons nu al helpen om anders te reageren op negatieve emotionele ervaringen van jongeren. Op momenten waarop jongeren moeite hebben om hun emoties te reguleren, kunnen we in plaats van te zeggen: "Laten we harder ons best doen", ook kunnen vragen: "Is er nog een andere manier om met deze emoties om te gaan?" In plaats van ons alleen te richten op het verminderen van de intensiteit van negatieve emoties, zouden we kunnen vragen: "Kunnen we ook bij andere emoties uitkomen?" Net zoals muziek niet alleen wordt bepaald door hoe hard die klinkt, maar ook door de dynamiek tussen het aanslaan van verschillende toetsen, moeten we emoties en emotieregulatie niet alleen begrijpen in termen van intensiteit, maar ook in termen van de type-specifieke dynamiek tussen emoties en tussen de manieren waarop we die reguleren. Aandacht voor type-specifieke emotiedynamiek kan de sleutel zijn tot het begrijpen van, en uiteindelijk richting geven aan, de melodieën van ons emotionele leven.

LIST OF PUBLICATIONS

Peer-Reviewed Articles

Lo, T. T., Pouwels, J. L., Vink, J. M., van den Broek, N., Eltanamly, H., Maciejewski, D. F., & Verhagen, M. (in press). Loneliness and Depressive Symptoms Within and Across Hourly and Half-Yearly Timescales: Testing the Evolutionary Theory of Loneliness. *Development and Psychopathology*. https://doi.org/10.31234/osf.io/pnuq4_v1

Lo, T. T., Verhagen, M., Pouwels, J. L., van Roekel, E., O'Brien, S. T., Debra, G., Braet, J., Vink, J. M., & Maciejewski, D. F. (2025). Emotion Differentiation in Adolescents: Short-term Trade-offs with Regulation Variability and Emotion Intensity. *Affective Science*, 6, 243-258. https://doi.org/10.1007/s42761-025-00301-4

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Lo, T. T., Van Lissa, C. J., Verhagen, M., Hoemann, K., Erbaş, Y., & Maciejewski,D. F. (2024). A theory-informed emotion regulation variability index: Bray–Curtis dissimilarity. *Emotion*, 24(5), 1273. https://dx.doi.org/10.1037/emo0001344

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Revise-and-Resubmit Manuscripts

Lo, T. T., Maciejewski, D. F., Vervoort, L., Vink, J. M., Cheng, T. N., Pouwels, J. L., & Verhagen, M. (2026). Negative Emotion Transitions May Have Immediate Benefits in Decreasing Negative Emotions in Daily Life. https://doi.org/10.31219/osf.io/7yqkw_v1

Hoffenaar, P. J., Leijten, P., van den Akker, A., & Lo, T. T. (2026). Learning the 'tricks of the trade': The role of experience in strategy repertoire and switching in infant soothing. http://dx.doi.org/10.2139/ssrn.6359728

Maciejewski, D. F., Erbaş, Y., Lo, T. T., Dejonckheere, E., Olthof, M., Bunge, A., & van Roekel, E. (2026). Emotion Characteristics and Emotion Regulation Dynamics in Daily Life: Evidence for Non-Linear Relations. https://doi.org/10.31234/osf.io/5u67v_v1

ABOUT THE COVER LOGO

The logo is based on ancient Chinese logograms (oracle bone scripts) that visually represent the concepts of heart and change (Figure C1 and C2; both extracted from Multi-function Chinese Character Database, https://humanum.arts.cuhk.edu.hk/Lexis/lexi-mf/).

Figure C1. Two early Chinese logograms, both representing the heart literally and emotion symbolically.

Figure C2. Early Chinese logogram representing changes.

The heart logogram symbolically refers to inner emotions. The cover logo (Figure C3) are stylized reinterpretations of two heart logograms (Figure C1). Their inverted relationship draws on another ancient logogram meaning change, originally depicted as the transformation of a person from an upright to an upside-down position (Figure C2). By placing the two heart forms upside down relative to one another, the logo symbolizes changes in emotions, the theme of this dissertation.

Figure C3. Cover Logo: Change in Emotions.

ABOUT THE AUTHOR

Tak Tsun (Edmund) Lo was born in 1990 in Kowloon City, Hong Kong. After completing his secondary education at La Salle College, he studied psychology at the Chinese University of Hong Kong. Following the completion of his bachelor's degree in 2012, he worked in an investment bank for several years before returning to psychology in 2016. In 2018, he completed a Master of Social Science in Clinical Psychology at the Chinese University of Hong Kong.

After completing his clinical training, Edmund worked as a clinical psychologist in a maximum-security prison. He later became a registered clinical psychologist on the Accredited Register of the Department of Health in Hong Kong, an associate fellow of the Division of Clinical Psychology of the Hong Kong Psychological Society, an Emotion-Focused Therapist certified by the International Society for Emotion Focused Therapy, and an EMDR therapist accredited by the EMDR Association of Hong Kong.

In 2021, Edmund began his PhD in Developmental Psychopathology at the Behavioural Science Institute of Radboud University. During his doctoral training, he joined several research groups, including Complexity in Behavioural Science, Emotion Reactivity and Regulation, and the Clinically Applied Research Lab. Since 2023, he has served on the Research & Education Subcommittee of the International Society for Emotion Focused Therapy. As a teacher, since 2020, he has delivered guest lectures and supervised 15 bachelor's students. During his PhD, he also served as a statistical consultant for full-time researchers at the Behavioural Science Institute.

In 2026, Edmund became a postdoctoral researcher at Radboud University. He also practices as a psychologist in The Hague and Rotterdam. Registered with the Nederlands Instituut van Psychologen (NIP), he primarily supports international students and expatriates in working through emotion-related difficulties. More information about his work can be found at https://taktsun.com.

ACKNOWLEDGEMENT

The sky is greyish but bright, and the air is wet with the morning mist that is so characteristic of springtime. The tree branches are empty, but when you look closer, there are little buds with tiny green tips, summoned by moisture and sunlight, yet still a bit conservative about fully showing themselves in this lingering chill. It is in this transitional weather that I am writing this acknowledgements section, also at a transitional juncture in my life. I have come to realize that there are so many people to whom I owe my gratitude.

On paper, a PhD is a terminal degree. To a PhD candidate, it is also a phase of life. To someone who hasn't been in the Netherlands, it is an adventure. So, allow me to lead you through this acknowledgement section as a personal journey.

Above all, I must thank my supervisors, **Maaike Verhagen, Jacqueline Vink, Dominique Maciejewski, and Loes Pouwels**. In the PhD journey section, we will arrive at the contexts in which I thank you! For now, I hope you won't mind that I start chronologically, from where it all began.

Where it All Began: My Family

Let me begin with a story about my grandfather, told by my mother. He was a woodworker who was exceptionally skilled at joinery, that is, fitting pieces of wood together seamlessly into furniture using nothing but the wood itself. My mother witnessed him playfully competing with fellow woodworkers. In these competitions, they would throw the chairs they had made from a height over and over again, first from the first floor, then the second, and so on. My grandfather's chairs were always the ones that lasted. He would proudly pick up the chair he had made, still intact, while the others had broken apart. My mother used to joke that because my grandfather was so serious and so good at his craft, he ended up being quite a poor woodworker, because his customers only ever needed to buy the same piece of furniture once. But he was proud of himself, and so was my mother. And so am I. I never met him, but I thank him for teaching me to be serious about what I do, and to be proud of it.

Alice, my mother, is meritocratic in a loving way. She believes in the beauty of things being done well, as they should be, or, in her words, "arriving at where they are, like how a gymnast lands on the floor with precision." It is probably from her that I developed the intrinsic motivation to do things well. It is not about getting to the top, but about doing things in the way they should be done. In her time, she and her peers had their education disrupted early in secondary school. Despite not having the chance to continue pursuing knowledge systematically later in life, she has always believed in knowledge. She has always encouraged us to pursue it and has been proud of us at every academic milestone. I thank her for giving me and my sisters all the room to develop ourselves intellectually,

while shouldering all the hard work of earning a living and putting meals on the table, in the absence of my father.

I thank my older sisters. Thank you, **Stella**, for believing in me from the time I was very young. You told me that you knew I could go far from the moment you saw me lining up little toy blocks in a row. As I have grown older, I have come to understand that it is often not talent that matters most, but the confidence instilled in a person that carries them through challenges and difficulties. Thank you, **Helen**, for showing me how to live a righteous life, for spoiling me sometimes, and for loving me as a little brother. You are the only sister with whom I would throw tantrums, and from whom I could successfully get what I wanted, though I do remember that I did not do that often. You always met me with patience and a smile.

Thank you, **Angela**, for showing our family that excellence is within our reach. Importantly, you have always carried that striving for excellence within yourself, but never placed pressure on us, your siblings, to match your achievements in the areas where you excelled. That said, from time to time, I still think what you have achieved is insurmountable. I understand, though, that you have invested extraordinary effort, perhaps more than any of us siblings, not only in your own achievements, but also in our family.

Every family has its own dynamics, and its own challenges. Without going into great length here, I noticed from a very young age that something about emotions felt off in our family. Not that we were not a loving family, or that we did not love one another, but that there were certain emotions, tied to very specific contexts, that were effectively forbidden at home. If emotions are destinations on a map, then there were small areas that, at least to me, remained unexplored and disallowed, as if they were obscured by a heavy mist. In their invisibility, I never knew how deep one might fall into them once entered, how steep the path was to arrive at or leave them, or what other landscapes they might lead to if one could pass through. When I was small, I only sensed that something was off, without having the words I now have to describe it.

If you cannot name something, you can hardly work on it. I grew up with a rather naive and simplistic problem-solving and outcome-fixated mindset toward behavioural problems and mental health: that there is always a "right" way to lead to a "good" outcome. When it came to emotion, I assumed that unpleasant feelings should be handled by following one best demonstrated path, much like focusing on landing precisely on the floor like a gymnastic does.

My Student Days

Bachelor

Although I had a simple heuristic for dealing with emotions, I was probably still puzzled by that sense of offness. Naturally, I was drawn to the study of psychology when I entered university. During my bachelor's studies, I was lucky to have **Freedom** Yiu Kin Leung as my thesis supervisor. True to his name, he gave me complete freedom to design my own research topic, study design, and run my own study. I am still proud of my bachelor's thesis: 180 participants signed up for an 84-day study in which they were encouraged to engage in gratitude thinking before going to sleep each night. For 84 days, participants completed daily diaries indicating whether they had practiced gratitude; they could still receive full remuneration even without doing so, as payment depended only on diary compliance. In addition, they evaluated each day how habitual their nightly gratitude practice had become. Beyond finding a perhaps unsurprising association between practicing more gratitude and greater increases in subjective well-being, I also found that the non-linear trend of habit formation in gratitude resembled that of other behavioural habit formation processes. It was this bachelor's thesis that first drew me into within-person change processes. And when I eventually applied for a PhD, Freedom supported my applications without reservation. Thank you, Freedom, for your guidance during my bachelor years and for enabling me.

After graduating from my bachelor's studies, I spent a few years at an investment bank, supporting financial derivative sales and traders. That bank, which, by the way, no longer exists, gave me a few bucks in my pocket. With that, I had a temporary financial freedom to decide more fully what I wanted in life.

Master

I was gravitated back to psychology once again. I continued with clinical psychology training. Clinical psychology training in Hong Kong has both great breadth and great depth. I am incredibly thankful to my teachers in the clinical programme, Sue, Chui-de, Agnes, Peter, Patrick, and Chee-wing ("Sum-Wong"), all scientist-practitioners with their own distinctive strengths, which together formed the breadth of the training. To this day, all of you still seem like superheroes to me.

Specifically,

- **Sue**, I thank you for your step-by-step, structured guidance in helping us build our clinical skills; later, when I started my PhD, you also generously shared with me how you walked the path of a clinician-researcher when we had a chance to meet in Groningen.

- **Agnes**, I thank you for encouraging me to attain the highest possible level of professionalism as a psychologist, by respecting clients through attention to the smallest details.

- **Peter**, thank you for leading us beyond a fixed approach to psychotherapy, and instead teaching us to look within and make ourselves into the approach.

- **Chui-de**, thank you for inspiring me with the sheer curiosity of a scholar, and for showing me how to enjoy reading the literature between the lines.

- **Patrick**, thank you for bringing us to examine the diagnostic manual through a developmental and history-of-science lens, so that we could understand how psychopathology has evolved within it and reflect on what psychopathologies are really like. And also, thank you for introducing me to Alma.

- **Sum-Wong**: Thank you for the scientific thinking, clinical skills, and care towards patients (students) you taught and demonstrated. Furthermore, your reflective attitude towards how to best contribute to the field constantly reminds me that I must do my best to keep learning and to contribute.

As a trainee, I completed more than 220 days of practicum in public hospitals and social services under the supervision of experienced clinical psychologists. I am immensely thankful to the clients I worked with during that time for trusting me and helping me see the complexity of mental health. My clients, together with my clinical supervisors, gave depth to my clinical training. I thank:

- **Crystal and my colleagues at HKCS**, for showing me how crucial multidisciplinary work is in bringing psychological services to the community; and that it begins with building a good climate among colleagues.

- **Robby**, for bringing love to child and adolescent clients before empowering them and their families through psychological services, and for teaching me that accessibility, that is, whether clients can understand it, is just as important as accuracy in assessment and treatment.

- **Joanna**, with whose help, support, and patience I came to understand how essential it is, as a psychologist, to earn idiosyncratic credits in working with clients and collaborating with colleagues.

- **Ide**, for showing me what phase-like and integrative psychotherapy can look like, and for planting in me the seed that I would need to learn more about emotion(-focused

therapy). Perhaps it was meant as a comment for professional growth, but I found out later how true it was for personal growth as well.

- **Ching**, for showing me by example how best to help a student, that was, me, learn from mistakes; for giving me all the support to explore clients' narratives together with them; and for giving me the freedom to grow from within.

I additionally thank **Alma**, who co-supervised my master's thesis with Patrick. In your project, you showed me how research and practice can go hand in hand. For my master's thesis, I worked with groups of older adults with type II diabetes. In community centers, I delivered group interventions to support their treatment adherence and strengthen their resilience in coping with illness-related distress. It was a project that put the biopsychosocial model of health into practice. With the support of you and your research team, I grew in independence in culturally adapting and implementing evidence-based group interventions, and also gained the opportunity to conduct intervention research. Importantly, you led me to observe what works beyond what the protocol says: a group intervention is not merely a one-way form of support from therapist to clients. It also forms a network of support among clients as they strive for a healthier lifestyle, body, and mind.

Here, I must also thank

- **Grace**, whom I have known since my undergraduate years, for introducing me to working with older adults through life review[1], and for warmly welcoming my family on the days we return to Hong Kong.

- **Cindy**, whom I have known since my high school years, for supporting me with sensitivity to applying to the clinical training and the continued journey in research and practice.

My Clinical Years

After my clinical training, I spent a few years in a maximum-security prison[2]—as a clinical psychologist serving inmates. I provided psychological services to local inmates as well as inmates of various nationalities and ethnic backgrounds from around the globe, of whom around 20% were non-local. Specifically, I (i) managed inmates' risks of self-harm through ongoing assessment, monitoring, and intervention; (ii) provided personalized treatment for their adjustment reactions and psychopathology (e.g., depression, anxiety, and prob-

1 Life review draws on person-defining memory episodes, from early life to the present, to form a meaningful and integrative narrative for older adults. This project later took on a life of its own through funding from CUHK and HKU.

2 I often make a long pause here in my presentations, and it has worked well as a joke every time.

lematic anger); and (iii) conducted psychological assessments and prepared reports for statutory requirements.

In these few years of full-time practice, I must thank:

- **Judy**, who patiently and carefully guided me through the process. One example was in perfecting the writing of psychological reports; every word we write can have a lasting impact on a person's life. It is not just about being professional, but also about showing respect toward the inmate and honouring our responsibility to safeguard society.

- **Daisy**, for showing me how to remain at ease, stay reasonably optimistic, and navigate a workable path in the intersections of organizations and people's differing goals.

- **Yvonne**, for being so supportive in exploring new ways to better serve inmates' needs together, and for keeping the spirit alive. On top of that, your enthusiasm for collecting data in practice to advance the service has led me to imagine that one day I could throw myself into doing the same.

- **Elsie**, my emotion-focused therapy trainer, for showing me through experience how emotions can be transformative for individuals, how much potential people have to grow from their emotions, and how one's emotions may become stuck in ways shaped by the environment.

Three Things I Learnt from Prison

There were three things that I learned from the prison environment. The prison environment was a special one in providing psychological services. There, inmates' (psychological) health is important, but before that, safety and security take priority. This was because safety and security were not taken for granted, but hard-earned; from time to time, there were successful malicious attempts to stir up conflicts and reintroduce antisocial practices[3]. We clinical psychologists were fortunate to be very well supported by the uniformed staff so that we could deliver our service smoothly. Nevertheless, this required us to plan every part of our service, especially new initiatives, with great care and caution. I suppose this later translated into being careful as a researcher when planning a study.

The second thing I learned is the importance of looking at dynamics and contexts. The correctional services are responsible for inmates' health. For inmates with a history or recent suicidal attempts, uniformed staff and we, psychologists, jointly monitor their

3 In this experience, even though I was not a prisoner, I came to realize how privileged many of us are to have lived most of our lives without needing to worry about safety and security, and therefore to have had the chance to thrive and grow.

well-being. The prison environment may not be the best place in which to stabilize, and stabilization proves especially difficult for inmates serving shorter sentences, for example, only three months. My supervisor, Judy, and my colleagues, Yvonne and Daisy, all experienced psychologists, shared their experience in doing this challenging work. Here, we focus on avoiding false negatives[4] among people at elevated risk, i.e., misjudging someone's risk as low when it is actually high. My supervisors and colleagues taught me that, to avoid false negatives, a one-time assessment of suicidal risk is almost never enough. More often, we needed longer, multi-informant observation to gain better assurance that an inmate's condition had stabilized. This lesson was seared into me one summer afternoon, when I received an urgent call from the uniformed staff that an inmate under my care had just made a suicide attempt, but had been saved by other inmates. It was a summer afternoon, but my spine turned ice-cold. In my first assessment with him, just one day earlier, I had actually formed the impression that his mood and behaviour were stable. It was so lucky that I did not plan to deviate from my colleagues' earlier teaching in recommending continued observation. How important it is to look for the within-person trend, and not rely on a single measurement in time! It was in the prison that I learned, in the most ultimate way, how within-person dynamics are central to understanding psychopathology.

The third thing I learned is that emotions are, among what can be observed, one of the most reliable cues for understanding people. Emotions are shaped by the environment, and prison is no exception. There, anger is useful: in an environment full of threats, being able to use anger to protect oneself can be key to survival. Obviously, this is not always a positive thing. Malicious individuals also instrumentalize displays of greater anger to get what they want. In this threat-rich environment, emotions like fear and sadness are often suppressed; expressing them may be interpreted as vulnerability[5]. This invites the prying eyes of malicious individuals. What I observed was not merely suppression, but an altered expression, or even experience, of emotions through anger. Many individuals I worked with who appeared at first sight to be angry men were in fact fearful of the environment or feeling powerless. Here, sustained, disproportionate, and context-incongruent anger is often the clearest indicator that there is something other than the presented anger that needs to be worked on. Compared to my two years of clinical training, which were more or less grounded in cognitive-behavioural principles, this emotion-focused approach was not only fresh but useful. Emotions can go with or without thoughts; some inmates were not good at putting their feelings into words; some chose not to; regardless, their emotions, whether expressed or suppressed, were observable. Even though I might not always work directly on emotions with an individual because of the purpose of the

4 We are well aware of false positives, that is, people appearing to be risky but in fact showing normal adjustment reactions because they have just arrived in prison.

5 Not all emotions are suppressed. Certain emotions, especially in specific contexts, are permitted. For example, grieving the loss of a family member, or being anxious about one's physical health.

encounter, for example assessment, or because of the individual's preference, emotions were always excellent cues from which to begin. In my therapeutic work, I witnessed how the change processes theorized in emotion-focused therapy, for example the transition from one negative emotion to another, such as accessing powerlessness beneath anger, can be profoundly powerful in facilitating psychotherapeutic progress and alleviating symptoms.

The focus on emotion opened up a new perspective for me in understanding both my clinical experience, including that across my five placements, and my personal experience: instead of the simplistic view that there is a "right way" and a "good outcome", there is so much more information in the dynamics of how emotions (in)vary over time. As with a gymnast, the landing cannot be understood in isolation; it is shaped by the ongoing adjustments made in mid-air.

Keen to learn more about within-person dynamics in emotions, I turned to scholarly search engines. On one side, the theoretical background of practice-oriented emotion-focused therapy was well developed, but its research on how emotional processes change was largely restricted to small-scale clinical case studies. On the other side, research using experience sampling method (ESM) data was gaining traction. In particular, interest was growing in describing how emotions change in daily life using ESM data, in which the same individuals self-report the intensity of different emotions in everyday settings 50 to 100 times over the course of a week. Both lines of research were exciting to read, but I was rather disappointed that there was not a closer connection between them. However, my disappointment quickly transformed into excitement, as I began to envision myself contributing to affective science by bringing these two sides a little closer together. It took quite some work, and quite some luck, before I embarked on my PhD journey in late 2021. A quick note of thanks to **Fanny** and **Venus**, both who helped me out in preparing for my PhD application!

The PhD Journey

The intellectual side of the journey has been well documented in the six main chapters. Here, I focus on expressing my gratitude.

Above all, I must thank **Maaike**. Thank you for daring to take on a PhD student whom you had only met online. I suppose that was fortunate for me, because you, and Dominique too, are prudent and cautious people, even among the researchers I have interacted with. Since the start of my PhD, you have been nurturing not only as my promotor and daily supervisor, but also as someone who supports my personal development. You gave me the freedom to be explorative, while patiently steering me toward steps that were prudent for completing my PhD. I am especially thankful for your support in helping me realistically plan how to return to work slowly and step by step after the arrival of my baby. My wife and I were fortunate to have a smooth delivery and reasonably manageable early months, but as I have seen the situations of my peers, some of them unfortunately much less smooth, I have come to appreciate how critical it is to make room for buffer when navigating transitions in life. I think this is a skill that will carry into the rest of my life, and I must say it is becoming increasingly important as I take on more responsibilities, whether as a psychologist who cares about knowledge and people's well-being, or as a person who cares deeply about family and friends. Your support for my personal development lasted right up to the final day of my PhD, when you, Dominique, and I had lunch together and reflected on what I could still improve in professionally communicating with others. Thank you for your mentorship over these years. I still look forward to your mentorship in the future, which continues in our current project.

Thank you, **Dominique**. You have taught me how to be daring in research, while also putting structure in place to make things happen. Professionally, you guided me as a supervisor, but relationally, you chose to relate to me as a collaborator from a very early stage of my PhD, indicating trust in my independence as a researcher. You have been constructive and supportive, but also the kind of peer who warns me away from potentially dangerous situations. Thank you for taking care of me at different conferences, and I feel lucky that we were able to attend some together, including the one in Washington, DC. Thank you as well for introducing me to your collaborators, and for being part of my first steps in settling into this place, including our walk with other colleagues in Rotterdam. These moments, though different in kind, all spoke to the same generosity with which you have supported me, both professionally and personally.

Jacqueline, I thank you for your strategic mind, your detail-oriented way of working, and the seriousness with which you attend to detail. You have shown me that attention to detail is part of how scholars make their first impression on others, or, put more plainly, how they gain credibility. I also thank you for gathering us in your home. Seeing how your daughter could turn a corner of that home into her own corner left a warm impression on me. It reminded me that a life in academia is not lived only through ideas and output, but also through the spaces we make for one another.

Loes, I thank you for your depth, your structural way of thinking, your accuracy, and your reliability. Thank you also for supporting me in carrying through the attempt of the XS grant, so that I could remain in the research arena. Your support helped make it possible for me to keep going, and I remain deeply grateful for that. Throughout my PhD, I would sometimes feel, and fear, that I had not prepared enough, and therefore was not making full use of what you know and of your supervision. To be honest, I still sometimes feel this way in our new project. But I suppose a pinch of these emotions may help propel our new project further!

Thank you to my roommates. Our research lines do not exactly overlap, but I am so glad that each of you has been part of my journey. **Daan**, it has been inspiring to watch you bring your chapters together, with plans and with successes. More importantly, thank you for letting me take part in different parts of your life over these years: the ceremonies, whether joyful or sentimental, the festivals, and the transitions. In return, my life in the Netherlands became richer than academic life alone. That meant a lot to me. **Andrea**, you are powerful, with a power that comes from within: in the way you fight for what is right, in the way you bring appreciation to those who do not automatically receive attention, and in the way you live and plan your life with a larger family. That has always been very cool to me. **Aafke, Thirsa, and Luca**, for many office days, the quick catch-up before the start of the day was always refreshing; and Aafke, thank you for joining the walk in Rotterdam. **Angela**, I am amazed by how well you grasp the dynamics between people and within a group, and thank you for caring to translate the Dutch way of things for me. Abele, Joëlle, Nina H., and Lise, we did not overlap much in time, but I was inspired by the way **Joëlle** enjoys experimenting with food made from what grows in your garden; and **Nina. H** and **Lise**, I thank you both for helping me in one of the final moments of panic when I was trying to decide on my dissertation title. **Abele**, your DIY spirit, your wide range of interests, and your many skills look to me like part of what a scholar can be. It was great fun going bouldering with you.

I also want to thank the philosophy office folks, including Merlijn, Freek, Sander, and Mihaela. **Merlijn**, I think you were the first Dutch friend I made on this journey. Your help has been quite substantial in shaping my path, perhaps even without your knowing it. First, in practical terms, you connected me with Josse and Michelle, who sublet their place to me. That made my life much easier in those first weeks of arrival. Second, you shared a very personal tip for doing good research, which was simply to sleep more. I still remember the sleeping bag in the office. This has been especially effective now that I have become a father. Third, your work, together with your colleagues', in showing that generalized dynamics in personalized assessments is possible has been a real source of inspiration for my own work. **Freek**, a friend in need is a friend indeed. Thank you for coming all the way from Groningen to help paint the wall, with Daan as well, for enjoying takeaway food with us afterwards, and for being open to exploring a theoretical-methodological thought piece with me. It did not become a proper manuscript, but many of those ideas now live on in the general discussion. **Sander**, the passion with which you speak about teaching every time, and how it gives you insight into research, has been inspiring to me, let alone your efforts in developing your own music production. **Mihaela**, as one of the CiBS folks, your way of working on your own line of work has also been a source of strength in reminding me that we can carry on with our ideas.

Thanks also to my next-door roommates. **Kirsten**, you were the very first colleague I spoke with when I started my PhD, and you made me feel welcome. **Suhaavi**, thank you for bringing us all together so well and for leading us to see the beauty of your culture and family, not only through your wedding, but also through the way you relate to us. **Nina B.**, thank you for being not only curious but also supportive of my attempts at food preparation, back when I was still living in Nijmegen. **Lisa**, thank you for sharing with me your little stories of reverse culture shock, such as friends noticing that you had picked up Dutch accents in your German, which helped normalize my own adjustment to this new culture. **Levie**, thank you for sharing to me your perspective in ageing, which opens up possibilities to me. **Calorta**, thank you for teaching me, along with others, dancing steps during the writing weeks, and for sharing your passion for contributing to the mental health of others. **Laila**, thank you for showing me how researchers can also develop and sustain their other talents, as in your drawing videos on YouTube. **Mili**, thank you for your love of horror stories, I still remember that ride to the writing week site where we took turns to tell horror stories! **Eveline**, thank you for showing me your discipline and calmness throughout the years. And **Anouk**, thank you for inviting me to take part in your cool work.

I also thank the members of the secretary office. **Christel**, perhaps the very first Radboud colleague I came into contact with. It was initially for arranging interviews, but even through those early exchanges, I already had the feeling that BSI at Radboud was a very nice and warm place. **Katja**, for the joy you brought, and for the jenever you recommended. **Lanneke** and **Ellen**, for your reliable help with all matters, big and small.

I thank other members of the department as well. **Maartje**, for the opportunity to teach, for the feedback you gave me, and also for helping with garlic cutting during one of the writing weeks. **Junilla**, for the warmth I always felt after hearing the little stories of daily life about your loving family. **Danique** and Harmen, for the opportunity to assist with teaching a course; and **Harmen**, thank you also for your practical tips on how to approach writing grant proposals.

I thank my co-authors. **Caspar**, thank you for the coffee at Westerpark, for sharing your story of becoming a scholar, and for showing me, through our work together, how to be assertive by well-articulated reasons. **Katie**, I have long looked up to the breadth of your work on emotion, your humble presence, and your precise yet stylish writing. **Yasemin**, thank you for showing me how open scholars should be to having their work discussed, and challenged. **Eeske**, thank you for generously allowing me to use your dataset and showing by example how to do team science. **Leentje**, thank you for the EMRRGO lab meetings, the treats there, and for broadening my angle to understand emotion research. **Hend**, thank you for showing me by example how to cut words elegantly while still keeping things gracious. **Jolien, Gillian**, and **Sarah**, thank you for being open to my invitation to use the dataset you have been working on, and for showing me the many facets in which the field of emotion and emotion regulation is still so needed. **Tin Nok (Daniel)**,

my peer in clinical training, thank you for helping me enrich my discussions as a clinician, and for accompanying me on this journey in scholarship, where almost none of our previous peers could accompany me. **Peter Hoffenaar**, for showing interests in my work and including me in yours. I also thank **Matteo, Peter Kuppens, Elisabeth**, and **Peter Koval** for generously granting me access to their ESM dataset.

I also thank a few lab groups. To the CiBS lab group, and **Fred** in particular: your work on RQA inspired me, perhaps unexpectedly, to see that there is much that can be done with distance dissimilarity, and this in fact helped shape my PhD; **Yingjie**, for the Nijmegen walks and meals that made me felt I belong to the city; **Jingmeng**, for the cultural specific jokes we could share during CiBS meeting, and your curiosity on why emotions matter a lot to me (you get a very detailed answer here!). To the EMRRGO lab, and **David** in particular: thank you for the chill vibe and for the compelling examples you shared in applying complexity concepts to the field. And to the Clinically Applied Research (CAR) lab members: the group's commitment to integrating research and practice has been crucial in keeping my own passion for this alive.

Speaking of passion, I must also thank the folks in the International Society of Emotion-Focused Therapy, near and far, who have supported me as well. **Judith** and **Elsbeth**, thank you for embarking on a journey with me in practice-based research; I am very much looking forward to what we will do together. **Juliette**, thank you for supporting my continued training in emotion-focused therapy in the Netherlands. **Carla**, and the other research and education subcommittee members, thank you for the opportunity for me to contribute. **Queenie**, thank you for showing confidence in my research work, for your support, and for the opportunity to share findings with your colleagues. **Jason**, thank you for sharing your three-identity journey as a researcher, teacher, and clinician. **Karli** and **Zhi**, my buddies in continual education in EFT. And I also thank those who have supported me from farther away, **Leslie, Jeanne, Robert, Rhonda, Laco, Antonio**, and **Ueli.** Your past and present work has been a source of inspiration throughout my PhD journey.

I also thank those who gave me opportunities to enrich my PhD. **Ava**, for connecting me with other amazing researchers. **Amy**, for trusting me so much in our collaborations on training, teaching, and projects. **Marjolijn, Lianne, Stella, Jo**, and **Kenneth** (Professor Kuen-Fung Sin), and **Enyi** for giving me the opportunity to learn about research and education on high-ability students. **William** and **Toon**, for giving me the opportunity to serve the RTOG.

As I said in the beginning, my PhD has been a phase of life. I am deeply grateful for all the buddies who have accompanied me through it: **Henry and Jeroen, Siu, Wongyu, KPK, Carlijn, Lu and family, Nuria and Adriaan, Teote, Gaia and John, Betty, the family of Rebecca and Maurice, the family of Gigi and Kaiwa, the family of Joel and Jean, the**

family of Aaron and Ursula, the family of Plato and Christine, Sunny and Loretta, Tina and family, Rod, Dee, and Hodar.

Last but not least, I thank my wife, **Yan Yin**, who has accompanied me throughout this entire journey, from the very beginning until now. You saw who I was before I realized it myself, and you saw who I could become before I became who I am.

This thesis is about what happens between moments, between emotions, but my PhD has also unfolded between life phases. By the time I am writing this paragraph, spring has fully arrived, and the flowers are wide open; the air carries the smell of freshness and life. Now that I carry with me the love and support of my family, friends, and teachers, I feel blessed, but also courageous, to take future steps in exploring both the map of emotions and the map of my life, whether the places are lit or unlit, and wherever they may lead me.