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DOI:
10.31234/osf.io/twk9m

Publication date:
2023

Document Version
Early version, also known as pre-print

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

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NOTE: This paper has been submitted for publication. It has not yet been peer reviewed. Draft version 2, 2023-09-18. Uploaded to PsyArXiv on 2023-09-18. OSF links are redacted as they are currently only available to reviewers. Supplemental materials available upon request.

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The study’s data, code, and output are available at https://osf.io/vzh2n/?view_only=[REDACTED]. This article reanalyzed data published in Blanke et al. (2020). All authors declare no conflict of interests. Katie Hoemann is supported by the Research Foundation – Flanders (12A3923N).

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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.

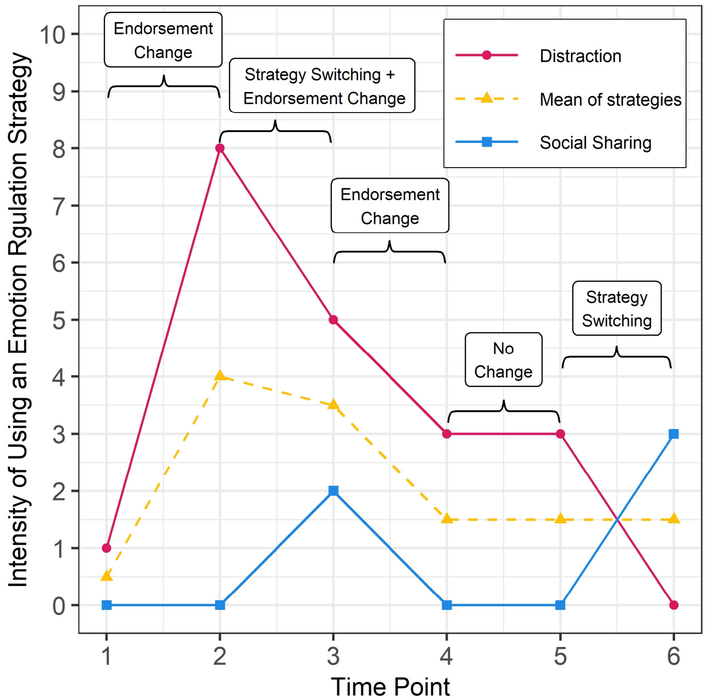
The Theoretical Foundation of ER Variability

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 1).

Figure 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 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 1); if no, Edmund reduces his overall intensity of ER (e.g., Time 3 to Time 4 in Figure 1). This example points out two important processes that are central in our understanding of ER variability, namely *strategy switching* and *endorsement change*.

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 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 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 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 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, 2013)[1]. *Replacement* in species refers to decreases in numbers in some species and increases in some others. This pattern of change may reflect the 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

[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.

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 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 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,

[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.

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/?view_only=[REDACTED]. 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 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

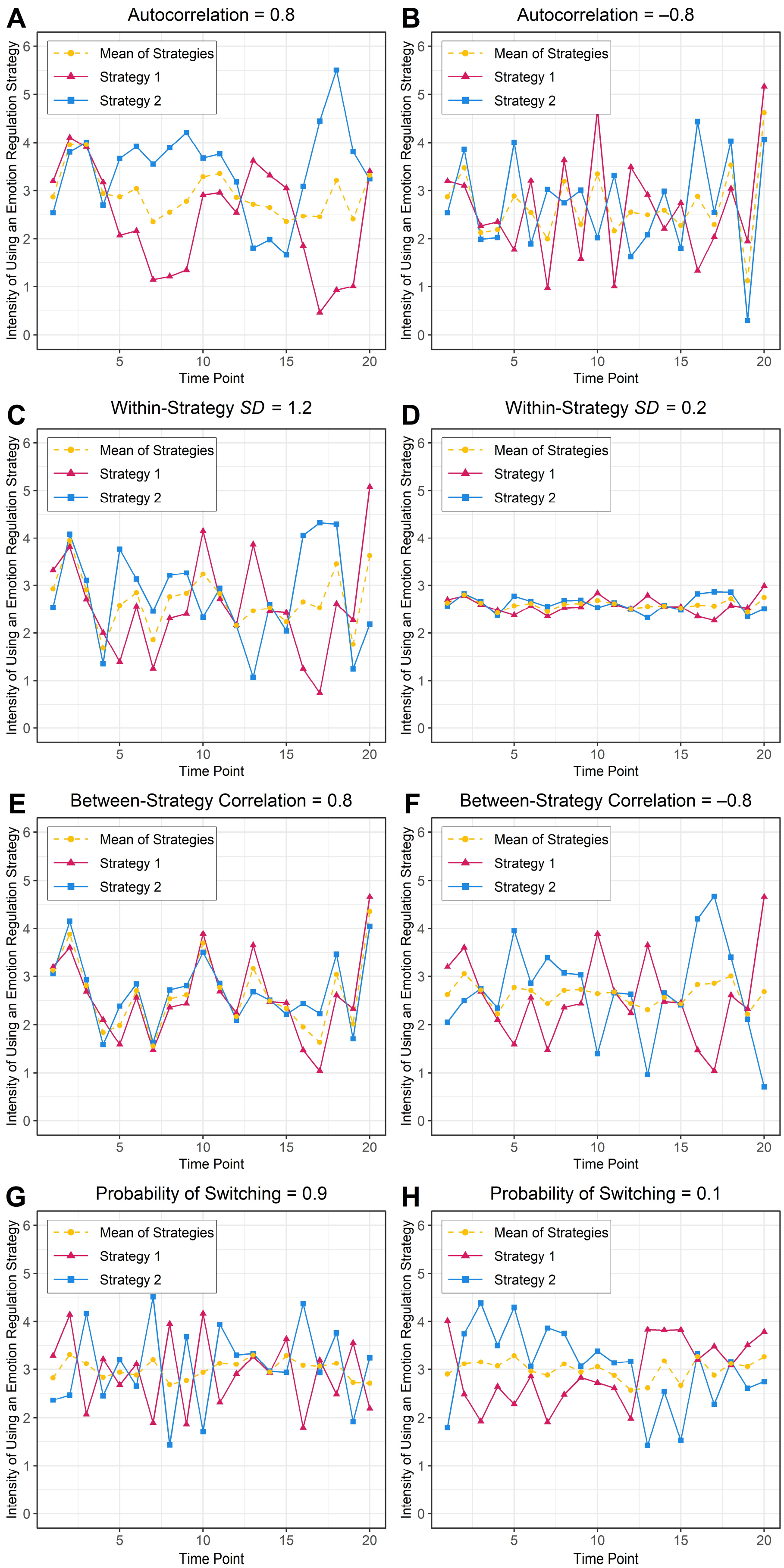
Simulation Parameters and Data Generation

Simulation 1: VAR(1) model. We set realistic values for five simulation parameters based on two ER experience sampling datasets (Blanke et al., 2020; Verhagen et al., 2022) [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 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.

Figure 2

Influence of Four Simulation Parameters on ER Variability Processes

[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; 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.


A
Autocorrelation = 0.8
B
Autocorrelation = –0.8
C
Within-Strategy *SD* = 1.2
D
Within-Strategy *SD* = 0.2
E
Between-Strategy Correlation = 0.8
F
Between-Strategy Correlation = –0.8
G
Probability of Switching = 0.9
H
Probability of Switching = 0.1
Mean of Strategies
Strategy 1
Strategy 2
Intensity of Using an Emotion Regulation Strategy
Time Point

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 2A). Similarly, the change of mean ER strategy ratings across time is small, indicating low endorsement change (Figure 2A; smooth dotted line). The opposite is observed when the autocorrelation is low, where both strategy switching and endorsement change are relatively high (Figure 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 2C). Similarly, the change of mean strategy ratings is relatively high, indicating high endorsement change (Figure 2C; spikey dotted line). The opposite is observed when the within-strategy *SD* is low, where both strategy switching

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

and endorsement change are low (Figure 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 2E; overlapping solid lines), but relatively high change of mean strategy ratings, indicating high endorsement change (Figure 2E; spikey dotted line). When the between-strategy correlation is low, there are relatively more strategy switches (Figure 2F; converging or diverging solid lines) but fewer endorsement changes (Figure 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 *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 2G), indicating high strategy switching. The opposite is seen when the probability of switching is low (Figure 2H), indicating low strategy switching. The mean of ER strategies randomly fluctuates regardless of the probability of switching (Figure 2G and 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). 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

[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).

replacement subcomponent and not the endorsement 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.

Table 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.

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.

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 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/.

Table 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.

Measures

Questionnaires. All datasets assessed NA items and ER strategies at each ESM observation (Table 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.

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 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].

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[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

Table 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.

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

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

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.

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 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.

Table 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.

Thirdly, 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.

Fourthly, 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 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 (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.

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