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Distancing alters the controllability of emotional states by affecting both intrinsic stability and extrinsic sensitivity

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eLife Assessment

This **important** manuscript proposes a dual behavioral/computational approach to assess emotional regulation in humans. The authors present **solid** evidence for the idea that emotional distancing (as routinely used in clinical interventions for e.g. mood and anxiety disorders) enhances emotional control.

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Abstract

Background

Emotion regulation strategies such as distancing are a core component of many evidence-based, effective psychotherapeutic interventions. They allow individuals to exert more 'control' over their emotional state. However, objectively disentangling how emotion regulation increases control has been difficult for reasons including a lack of a coherent theoretical framework for emotion control and insufficient experimental control over external inputs. Here, we apply a well-established theoretical framework for controllability to a tightly controlled experimental setup to examine the computational mechanisms by which emotion regulation interventions enhance emotional controllability.

Methods

109 participants were randomized to either a short emotion regulation intervention (distancing) or a control intervention. Both before and after the intervention, participants reported their emotional state along five dimensions repeatedly while watching a series of short, standardized, emotional video clips. A Kalman Filter was used to quantify how multidimensional emotional states changed with video inputs. The consequences of the

emotion regulation intervention were examined by Bayesian model comparison, comparing models allowing for a change in intrinsic dynamics and/or input weights. Controllability was quantified using the controllability Gramian.

Results

The Kalman filter captured participants' emotional trajectories, showing that emotional states were affected by the emotional videos; persisted; and interacted with each other. The distancing strategy made emotional states less externally controllable. It did so by altering two aspects of the dynamical system: by stabilizing specific emotional patterns and by reducing the impact of the external video clips.

Conclusions

Our study used a novel approach to examine emotion regulation, finding that a brief distancing intervention increased perceived emotion control by reducing how much external stimuli can control emotional states. This is due to both an increase in the intrinsic stability of certain emotional states; and a reduction of the sensitivity to certain extrinsic affective stimuli.

1 Introduction

Psychotherapeutic interventions are effective treatments for depression and anxiety, but the mechanisms of action responsible for these effects remain poorly understood (Kazdin, 2007; Carey et al., 2020). In addition, there is considerable variation between individuals regarding treatment response (Goldfried, 2013). Better targeting psychotherapeutic interventions according to individual needs or characteristics might improve therapy effectiveness. This requires understanding how existing psychological treatments work and for whom they work.

Previous research studying the mechanisms underlying psychological treatments has mostly focused on changes after the complete treatment courses (Klug et al., 2012). However, psychotherapeutic treatments are complex interventions involving different components (Luborsky et al., 2002), likely affecting different behavioural processes and acting via different mechanisms. As such, changes observed after the full course of treatment reflect the many many aspects of the intervention. In contrast, little research exists on how different components engage specific mechanisms.

In this study, we build on recent suggestions (Reiter et al., 2021; Wolpert et al., 2021; Holmes et al., 2018) and a promising new research direction (Brown et al., 2021; Huys et al., 2022; Dercon et al., 2023; Norbury et al., 2023), using cognitive computational techniques to study isolated interventions. This approach aims to better characterize and understand the change mechanisms of specific, key psychotherapeutic interventions. Specifically, we examine the effect of distancing—an emotion regulation technique—on the dynamics of emotions.

Emotion regulation strategies are an essential element of many psychotherapeutic treatments (Gross, 1998). Some emotion regulation strategies can alleviate symptoms of mood disorders and generally improve well-being (Berking et al., 2013; Boemo et al., 2022; Powers and LaBar, 2019; Somerville et al., 2022). Here, we define emotion regulation as using explicit strategies to intentionally up- or down-regulate positive or negative emotions. Effective strategies include problem-solving, reappraisal, acceptance, and distancing techniques (McRae and Gross, 2020; Webb et al., 2012). Distancing involves simulating a new perspective to increase the psychological distance from an event or situation and, with that, the emotional impact of a stimulus (Powers and LaBar, 2019; Webb et al., 2012). Distancing has been shown to reduce selfreported emotional experience reliably (Koenigsberg et al., 2009; Vrticka et al., 2012; Winecoff et al., 2011, 2013) and is associated with decreased amygdala activity even beyond the period of active regulation (Eippert et al., 2007; Walter et al., 2009; Domes et al., 2010). Distancing techniques are practical because they can be implemented in various situations with relatively low attentional demands and behavioural disruption (Powers and LaBar, 2019). We focus on distancing to gain insights into the mechanism of this specific treatment component in the hope of better understanding some of the complex processes underlying psychotherapeutic treatment effects.

Furthermore, emotion regulation research has mostly focused on the effects on individual emotions. Different emotions, however, are often related and influence each other. For instance, sadness can increase the likelihood of experiencing anger while emotions of different valence or arousal tend to inhibit each other: inducing happiness reduces experienced sadness, yet mixed states with both sadness and happiness can also occur. These interactions induce temporal dependencies between emotions, meaning that emotional states as a whole form a dynamical system fluctuating over time (Malamud and Huys, 2024; Durstewitz et al., 2020; Kuppens and Verduyn, 2017; Lange et al., 2022). As such, emotion regulation may be best conceptualized as the regulation of a dynamical system of emotions rather than as involving the regulation of individual emotions in isolation.

In recent years, network models have been developed to account for the dynamical systems properties of emotions (Borsboom and Cramer, 2013; Bos et al., 2017; Bringmann et al., 2013; Epskamp et al., 2018). This work has identified individual differences in affect dynamics which are linked to mood disorders (Bringmann et al., 2016; Kuppens et al., 2012; Pe et al., 2015, 2016; Sperry et al., 2020; Trull et al., 2015; Leemput et al., 2014). For example, increased inertia (temporal autocorrelation or how well an emotion can maintain itself) of negative affect has been identified in people with depression (Brose et al., 2015; Houben et al., 2015; Kuppens et al., 2010; Koval et al., 2012, 2013). Most interestingly, it has been suggested that there are discrete stable states (e.g. a depressed vs a happy state), so-called attractor states, between which people can transition (Durstewitz et al., 2020; Leemput et al., 2014; Wichers et al., 2016; Kuppens et al., 2012; Hosenfeld et al., 2015). Within an attractor state, the system is usually resistant to change, and under small disturbances (e.g. a stressful week), a person converges back to the current attractor state. A transition to another attractor state may occur if a perturbation is large enough or accumulated over time (Nelson et al., 2017). The transitions between states in a dynamical system are influenced by two important factors: the system's intrinsic characteristics and its sensitivity to external driving forces.

Past work mostly focused on dynamical properties inferred from the emotion self-reports alone and has often neglected the role of external factors (Boemo et al., 2022; Malamud and Huys, 2024). This is a critical omission as the dynamical properties of a system are not fully identifiable unless the inputs are known — inputs can nearly arbitrarily alter the apparent dynamical system. For instance, persistent sad mood could be due to a constant external stimulus producing sadness rather than due to an internal persistence of sad mood. Ignoring the immediate context within which emotions fluctuate may hence lead to wrong conclusions about the underlying affective system. Indeed, it is well known that external stimuli profoundly impact the dynamics of emotional states, particularly in laboratory settings (Asutay et al., 2022; Rutledge et al., 2014; Villano et al., 2020; Vanhasbroeck et al., 2022).

Since both the natural changes in emotions over time and the impact of external factors on emotions are important, there is a compelling rationale to explore the potential effects of emotion regulation on these two key aspects of emotion processes. By doing so, we can gain valuable insights into the mechanisms underlying emotional regulation and better understand how emotions are controlled. Understanding which emotions can be most effectively changed through a certain techniques can provide clearer insights into the targeted effects of such interventions. Additionally, identifying reliable indicators of whether the emotional system is resistant or adaptable to changes could open up possibilities for creating personalized interventions.

Therefore, our aim was to examine the dynamic network effect of emotion regulation, specifically by considering an individual's immediate context. We positioned emotion regulation within the framework of dynamical system theory and utilized tools from control theory to characterize the overall control properties of the emotional system. To briefly explain, a dynamical system is a series of linked differential equations (Brunton and Kutz, 2019; Durstewitz et al., 2020), each describing how one variable (here an emotion) changes over time. It permits emotions to influence each other and exhibits rich dynamical properties. The equations can incorporate the concept of control by allowing an input to drive one or more variables. Controllability, in this context, is a characteristic that depends on both how sensitive the system is to inputs and its inherent dynamics. It reflects how easy or hard it is to drive the system towards certain states. For instance, if all emotions are positively linked to sad mood, then a happy state would be challenging to achieve, reducing the system's controllability of single emotions.

In this study, we investigated how external emotionally-charged inputs influenced self-reported emotions over time (across multiple dimensions), and whether these inputs were essential to explaining the evolution of a rich, multidimensional emotional state. This enabled us to formally examine the impact of a distancing intervention on emotion dynamics whilst disentangling effects on intrinsic dynamics from alterations of external inputs. We also examined whether intervention-induced changes were moderated by measures of depressive or anxiety symptoms or difficulties in regulating emotions.

2 Methods

2.1 Participants

109 participants 18 years or older with current UK residence were recruited online on Prolific Academic (*www.prolific.co*). Prolific is widely used and reliable platform for online research due to its diverse participant pool and robust quality control measures (Peer et al., 2017; Palan and Schitter, 2018).

An a priori power analysis based on data from a pilot study estimated a minimum sample size of N = 109 (cf. Supplementary Materials D Power Analysis).

2.2 Procedure and Task

After indicating interest in the online recruitment platform, participants were forwarded to an electronic form of the participant information sheet. They could then provide electronic consent through an online form before being redirected to the experiment. The study duration was approximately 45 minutes, and participants were reimbursed £7.50/h through Prolific Academic after completion of study procedures.

In the experiment (**Fig. 1**), participants saw a sequence of short emotional video clips, each lasting 2–10 seconds and chosen for their efficacy in eliciting certain emotions. Video clips were from a previously-published database, with validated emotion ratings across multiple categories (cf. 2.2.2 Emotion-Inducing Stimuli; Cowen and Keltner 2017). After each video clip, participants reported their current emotional state in terms of two positive (amused and calm) and three negative emotions (disgusted, anxious, and sad). Emotions of disgust, anxiousness, and amusement were chosen as they were thought to be highly sensitive to video clip inputs. Conversely, sad and calm appear to be more persistent emotions which we expected to be informative about stability. Participants were instructed to use a slider to indicate how strongly they felt each of the emotions at that moment in time, with options ranging from “not at all” to “very”. Participants had 30 seconds to report their emotional state. If they did not manage to rate all emotions within 30 seconds, the experiment moved on to the next video without their completed rating.

After watching the first block of 54 video clips, participants were randomized to undergo either a distancing (emotion regulation) or a relaxation (control) intervention (cf. 2.2.1 Intervention). Following the intervention, participants watched a second block of 54 video clips and again rated their emotions after each video. A different set of video clips was shown, but the sequence of emotions targeted was matched to the first block.

2.2.1 Intervention

The emotion regulation intervention was based on a distancing appraisal strategy, i.e. “Leaves on a Stream” (adapted from Hayes et al. 2006). This technique involves viewing emotions and thoughts as events passing through one’s mind rather than getting “sucked in” by them. The script employed a visualization strategy, instructing participants to imagine they were standing by a stream with leaves floating gently past them. They were then told: “When an emotion or thought comes up, imagine you place the thought on one of those leaves and that you are watching the leaf - carrying your emotion or thought - float away, disappearing behind a corner or in the distance.” In the control intervention, participants were asked to engage in a relaxation exercise. They were told the same storyline as in the distancing intervention but without connecting the stream and leaves to their emotions and thoughts (the full text of both interventions is reproduced in the Supplementary Materials A Intervention Text).

Furthermore, in the group allocated to the distancing intervention, the phrasing of the question about their feelings in the second video block reminded participants about the intervention, stating: “You observed your emotions and let them pass like the leaves floating by on the stream.” This was not the case for the control group.

To reduce demand effects, the instructions were framed to suggest that the experiment was attempting to understand *whether* the distancing was helpful or not, i.e. participants were explicitly encouraged to report that the intervention was not helpful if they did not perceive it as effective.

2.2.2 Emotion-Inducing Stimuli

The emotion eliciting video clips stem from a validated database (Cowen and Keltner, 2017) (*https://s3-us-west-1.amazonaws.com/emogifs/uncensored.html*). This study analyzed emotional responses to 2,185 short videos, identifying 27 distinct emotional experiences categorized through a survey completed by 853 English-speaking US participants. The videos were collected from online sources depicting diverse emotionally significant situations, including cute animals, natural landscapes, distressing scenes such as feces and vomit, accidents and dangerous stunts, and many others.

For our experiment, we selected video clips that fit into five target emotion categories: Amusement/Joy, Disgust/Horror, Sadness/Sympathy, Calmness/Aesthetic Adoration, and Anxiety/Fear. We chose clips that showed a high mean and a low entropy in the ratings from Cowen and Keltner (2017) for these emotion categories, to ensure they would specifically evoke the intended emotion. We identified 20 videos from each of the five categories, resulting in a total

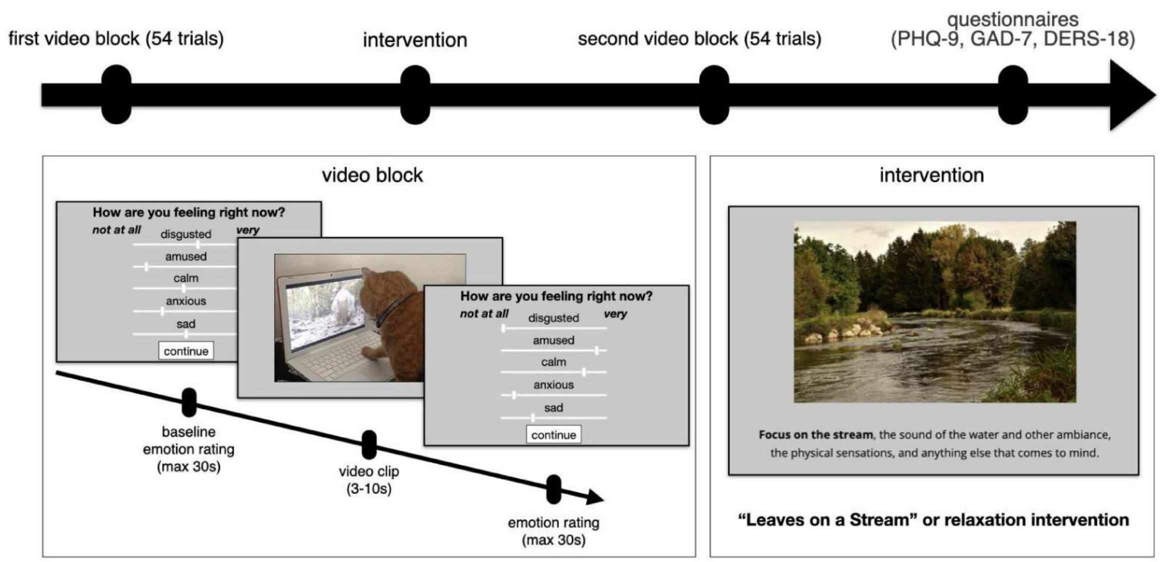


Figure 1

Task Description

The large arrow at the top displays the course of the experiment. Both video blocks comprised 54 video clips (2–10 seconds), and after each video clip, participants had 30 seconds to rate their emotional experience based on five emotions. Both blocks also had a baseline emotion rating before the videos started. Participants underwent either a distancing (emotion regulation) or a relaxation (control) intervention between the two video blocks. After the second block of video clips, participants completed three standardized psychological questionnaires measuring symptoms of depression (PHQ-9) and anxiety (GAD-7) and emotion regulation difficulty (DERS-18). PHQ-9: Patient Health Questionnaire. GAD-7: Generalized Anxiety Disorder Assessment. DERS-18: Difficulties in Emotion Regulation Scale.

of 100 videos. The ratings from Cowen and Keltner (2017) for each chosen video and the mean ratings over videos from an emotion category are shown in Supplementary Materials B Video Clips **Fig. B.2**, respectively **Fig. B.1**.

2.2.3 Study Sequence

In total, each participant viewed 54 video clips before and 54 video clips after the intervention. The video order was pseudorandomized for the first half. In addition, two randomly chosen videos were repeated three times within the first block to investigate the reliability of the ratings. The second block of videos contained different video clips, but the sequence of target emotions was the same as in the first block (including the repeated videos). All participants saw the identical video clip sequences, but before and after intervention sequences were counterbalanced across participants. Participants provided 110 ratings in total (55 before and 55 after the intervention) including a baseline rating before the first video of each block. The length of the experiment was based on simulation and recovery work (cf. Supplementary Materials C Experimental Design).

2.2.4 Self-Report Measures

At the end, participants were asked to complete three self-report questionnaires. To assess depressive and anxiety symptoms, we used the Patient Health Questionnaire (PHQ-9; Kroenke et al. 2001) and the Generalized Anxiety Disorder Assessment (GAD-7; Spitzer et al. 2006), respectively. In addition, we used a short version of the Difficulties in Emotion Regulation Scale (DERS-18; Victor and Klonsky 2016) to assess participants' ability to identify, accept, and manage their emotional experiences. The questionnaires were conducted after the experiment to prevent them from affecting participants' behaviour during the study.

2.2.5 Attention Checks

To maintain and monitor attention, participants were asked to detect a black cross, which could be shown briefly before the video clip started. 10 such attention checks were included, 4 in the first block and 6 in the second. Participants with an accuracy of less than 70% on the attention checks were excluded.

2.3 Computational Modelling

During the experiment, we asked participants to report their emotions after watching each video, resulting in a sequence of emotional state reports. To capture the temporal structure of this data, we used a linear Gaussian state space model, specifically the time-invariant Kalman Filter (Durbin and Koopman, 2012; Roweis and Ghahramani, 1999). This model is simple and tractable, accounting for possible errors in participants' self-reports and allows for external inputs that might influence their emotions. Essentially, this model helps us track the true emotional process as it evolves based on the participants' reports.

The Kalman Filter suggests an underlying latent process, referred to as the true emotional process, evolving in response to a sequence of emotional state reports $\mathbf{x}_t t = 1^T$ conditional on video inputs $\mathbf{u}_t t = 1^T$ (cf. to **Fig. 2A**).

$$\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{h} + \mathbf{C}\mathbf{u}_t + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}(0, \boldsymbol{\Sigma}) \tag{1}$$

$$\mathbf{x}_t = \mathbf{z}_t + \boldsymbol{\eta}_t \qquad \boldsymbol{\eta}_t \sim \mathcal{N}(0, \boldsymbol{\Gamma}) \tag{2}$$

The latent (unobserved) emotional state vector $\mathbf{z}_t$ comprises the activation of each emotion category z_t^i at time t. These latent emotions are assumed to evolve according to a discrete, linear first-order Markov process. The matrix $\mathbf{A}$ defines the dynamics matrix, which captures the degree to which an emotion carries over from one time point to the next and the degree to which it predicts future emotions. The matrix $\mathbf{C}$ captures the impact of videos, with the entry C_{ij} capturing the impact of a video of category j on emotion category i. The video category shown at each time point was identified through one-hot labelling in the binary input vector $\mathbf{u}_t$, i.e. each video was identified in the vector $\mathbf{u}$ by the main emotion it was targeting. The subjects' ratings x_i on each category i were mapped directly onto the latent emotion states z_i. Critically, however, Gaussian noise was added to both the latent temporal evolution and the observation processes with separate diagonal covariances $\mathbf{\Sigma}$ and $\mathbf{\Gamma}$, respectively. This is one of the key differences to standard emotional time-series analyses (Borsboom et al., 2021), in that this explicitly allows for noise or errors in the emotion ratings, and this noise can be 'smoothed over' through the filtering process.

2.3.1 Model Comparison

To understand the dynamics of the emotion reports elicited by the video sequences, we asked whether the different components of the Kalman Filter were indeed necessary to provide a parsimonious account of the observed data. To do this, we built increasingly complex models. The simplest model included only Gaussian noise, i.e. it assumed emotion ratings varied randomly over time. The next model additionally contained either a dynamics matrix ($\mathbf{A}$), an input weight matrix ($\mathbf{C}$) or both. The most complex model included a dynamics matrix ($\mathbf{A}$), an input weight matrix ($\mathbf{C}$) and a bias ($\mathbf{h}$). Additionally, we examined variations of these models where we constrained the input matrix $\mathbf{C}$ to be diagonal. Finally, models were fitted separately to each individual's emotion time-series using the python package *Pykalman* (*https://pykalman.github.io/*).

We calculated the Bayesian Information Criterion (BIC; Schwarz 1978) for each individual for each model based on an individual's model loglikelihood by penalizing for the number of parameters in the model. Models were then compared using the BIC at the group level. Cumulative model weights for the most parsimonious model are computed as a proportion of the total amount of predictive power provided by the full set of models contained in the model being assessed: $\omega_j = \frac{e^{-\Delta BIC_j}}{\sum_{i=1}^{N} e^{-\Delta BIC_i}}$ where $\Delta BIC_i = BIC_i - min(BIC)$, j indicates the most parsimonious model and N the number of models.

2.3.2 Stability

After extracting the parameters of the most parsimonious model, we investigated the eigenstructure of the dynamical system. Briefly, a linear dynamical system where variables interact, like the Kalman Filter model, can be decomposed into separate systems of non-interacting variables. This is achieved through an eigendecomposition of the dynamics matrix. By projecting the vector of state variables $\mathbf{z}$ on each of the eigenvectors, new combined state variables $\tilde{\mathbf{z}}$ (*eigenmodes*) can be defined, which evolve independently, i.e. no longer interact. Hence, these new combined state variables identify the effective emotional combinations which determine the evolution of an individual's affective state. The eigenvector corresponding to the largest eigenvalue of the dynamics matrix $\mathbf{A}$ identifies the most stable combination of emotions. In contrast, the eigenvector corresponding to the smallest eigenvalue identifies the combination of emotions that is most transitory and least persistent (for an example cf. **Fig. 2B-D**).

2.3.3 Controllability

Next, we investigated the controllability of the dynamical system. A system is more controllable if smaller inputs $\mathbf{u}$ are required to move its state $\mathbf{z}$ to any required value. We computed the controllability Gramian (C) for each participant as follows:

$$\mathcal{C} = [\mathbf{C} \quad \mathbf{AC} \quad \mathbf{A}^2\mathbf{C} \quad \dots \quad \mathbf{A}^{n-1}\mathbf{C}] \tag{3}$$

The controllability Gramian (C) combines the dynamics matrix ($\mathbf{A}$) and the weights of the external input ($\mathbf{C}$) to the dynamical system. If the rank of this controllability matrix is equal to the system's dimension, the system is controllable. A controllable system means that any state $\mathbf{z}$ can be achieved through the appropriate choice of external inputs $\mathbf{u}$. *How* controllable the system is captured by the strength of input $|\mathbf{u}|$ required. We investigated the characteristics of the controllability Gramian using singular value decomposition. Unitary vectors of the controllability Gramian define an energy ellipsoid (**Fig. 2E**). Unitary vectors corresponding to higher singular values identify the more controllable directions in the state space and vice versa. The more controllable a direction is, the less input energy is required to steer the system in that specific direction. In other words, an input of a given strength $|\mathbf{u}|$ can move the system further in a direction which aligns with a more controllable direction than a less controllable one.

2.4 Statistical Analysis

We used one-sided two-sample t-tests to test whether the emotion ratings averaged over video clips from the same video category for the emotion which was aimed to be elicited were higher than for the other emotions. In addition, two-sided one-sample t-tests were performed to test whether the mean emotion ratings, autocorrelation coefficients, and cross-correlation coefficients of emotion time-series significantly differed from zero. Those tests were all conducted on data before the intervention.

To investigate intervention effects, the principal analyses was a two-sample Hotelling T^2 tests to compare multivariate variables (e.g. eigendirections) between groups after the intervention. The randomized group allocation allowed us to focus on potential effects after the intervention. We also performed multivariate ANOVAs (MANOVAs) to test for an interaction effect between time (before and after intervention) and group. To zoom into single emotions, we used non-parametric tests because most dynamical and controllability features were not normally distributed. Mann-Whitney U tests were conducted to compare emotion variables, such as mean emotion ratings and eigenvector directions, between the intervention groups and one-sample Wilcoxon signed-rank test to compare variables before and after the intervention within an intervention group.

Multiple linear regressions were performed to investigate associations between emotion dynamics (dependent variable; DV) and symptoms (independent variable; IV) controlling for the intervention group (G): $DV = \beta_0 + \beta_1 IV + \beta_2 G$. Finally, to investigate whether psychological well-being moderated the effect of the intervention on emotion ratings, we examined the interaction effect between symptom score and intervention group: $DV = \beta_0 + \beta_1 IV + \beta_2 G$. All variables were z-scored for the regressions. For all above-mentioned analysis types, we used Bonferroni-correction to correct for the number of conducted tests.

3 Results

3.1 Participants

109 participants completed the experiment, but one participant was excluded due to attention check failure. Analyses hence focused on, 108 participants (57 randomized to the distancing intervention).

3.2 Eliciting Complex Emotional States With Videos

In the first video block before the intervention, each video induced the dominant (targeted) emotion as intended (**Fig. 3A**). Changes in the dominant emotion ratings for each video were significantly higher than changes in other emotions ($t \in [5.9, 26.2]$, all $p < 0.001$; **Fig. 3B** and Supplementary Material **Table I.2**). This shows that the sequence of emotional videos reliably

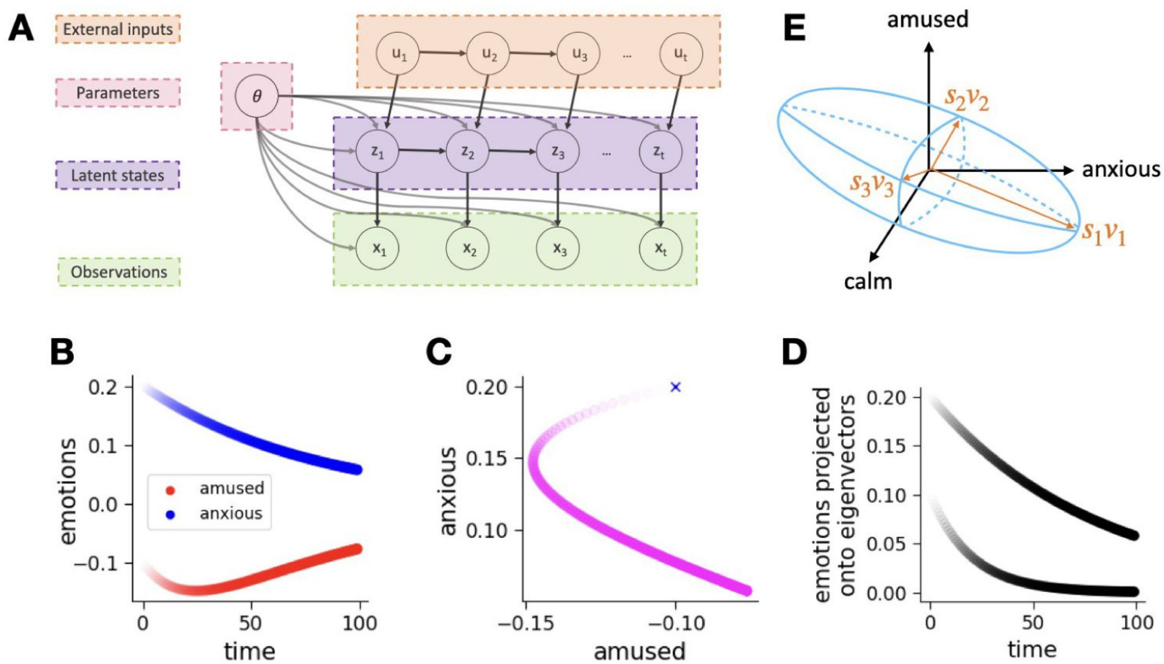


Figure 2

Dynamical System and Controllability

A) shows a graph visualization of the linear dynamical model, including external inputs ($\mathbf{u}_t$; emotional video clips). $\mathbf{z}_t$ describes the latent (unobserved) emotion states evolving based on a Markov process and directly mapping onto the acquired emotion ratings $\mathbf{x}_t$. **B)** shows the trajectories of a two-dimensional system (ratings of "amused" and "anxious") starting from a randomly chosen initial point without external inputs. Whereas anxiety decays independently of amusement, amusement is influenced by anxiety and thus, the trajectory of amusement is more complex and does not simply exponentially decay to zero. However, the more anxiety decays, the more the influence of anxiety on amusement decreases; and both variables converge towards zero. **C)** shows the trajectory of both emotion ratings plotted against each other. The blue x indicates the starting point. **D)** displays the independently evolving trajectories of the transformed variables $\tilde{\mathbf{z}}$ resulting from the projection of the state variables $\mathbf{z}$ onto the eigenvectors of the dynamics matrix **A**. **E)** The unitary vectors (**V**) of the controllability matrix define an energy ellipsoid where the unitary directions corresponding to higher singular values (**S**) are more controllable and vice versa. That means with the same effort one can go further into the most controllable direction ($\mathbf{v}_1$) and least far into the least controllable direction ($\mathbf{v}_3$)

induced the targeted emotions. The correlation between our participants' emotion ratings and those reported by Cowen and Keltner (2017) was moderate to strong across all emotion categories, with correlations of $r = 0.74$ for Disgust/Horror, $r = 0.65$ for Amusement/Joy, $r = 0.5$ for Calmness/Aesthetic Adoration, $r = 0.71$ for Anxiety/Fear, and $r = 0.6$ for Sadness/Sympathy (all $p < 0.001$). Thus, we replicated the ratings from Cowen and Keltner (2017) reasonably well.

Furthermore, changes in emotions other than the dominant one within a video category were significantly different from zero ($|t| \in [5.1, 19.3]$, all $p < 0.001$; **Fig. 3B** and Supplementary Material **Table I.2**). This indicates that the videos induced complex and multi-faceted emotional states. We also observed that emotional responses had a dynamic component. This was evident in the autocorrelation of each emotion rating, where an effect of the previous time-point is apparent during the rating of the next video ($AR(1) \in [0.07 - 0.25]$, all $p \leq 0.001$; cf. **Fig. 3C** and Supplementary Material **Table I.3**).

Dynamic effects can also be observed in the cross-correlation between emotion time-series showing that emotions interact with each other ($|r| \in [0.28 - 0.52]$, all $p < 0.001$; cf. **Fig. 3D** and Supplementary Material **Table I.4**).

Finally, the test-retest reliability of emotions elicited by repeated video clips varied accordingly to emotion type. Specifically, it was observed to be good for Amusement/Joy (video sequence 1: $ICC(2, 1) = 0.79$, $CI = [0.69,0.86]$, $p < 0.001$, video sequence 2: $ICC(2, 1) = 0.8$, $CI = [0.69, 0.87]$, $p < 0.001$) and moderate for Disgust/Horror (video sequence 1: $ICC(2, 1) = 0.59$, $CI = [0.43, 0.72]$, $p < 0.001$, video sequence 2: $ICC(2, 1) = 0.59$, $CI = [0.43, 0.73]$, $p < 0.001$).

In summary, the experimental setup resulted in reliable elicitation of complex, high-dimensional emotional states, allowing for the joint characterization of emotional input sensitivity and emotion dynamics.

3.3 Establishing a Dynamical Model

We next examined the dynamical properties of the emotion ratings, and the interaction with the emotion inputs using a Kalman Filter. First, we compared different models based on the group-level BIC to evaluate which dynamical components are required to capture the data over the whole experiment, i.e. the concatenated time-series before and after the intervention (**Fig. 4A**). We found that the most parsimonious model, carrying 99% of the cumulative model weight, included a dynamics matrix $\mathbf{A}$, a full input weight matrix $\mathbf{C}$ and diagonal noise covariances $\mathbf{\Sigma}$ and $\mathbf{\Gamma}$. Importantly, data generated from this model accurately captured the observed data sequences as shown in the blue-shaded part in **figure 4C**. Hence both external inputs and intrinsic dynamics are required to explain the self-reported emotion ratings. The recoverability of the matrices $\mathbf{A}$ and $\mathbf{C}$ in the most parsimonious model is shown in Supplementary Materials F Parameter Recovery.

3.4 Effects of Distancing on Emotional Responses

We first examined the effect of the intervention on the multivariate reported emotions averaged over trials (**Fig. 5A**). The mean ratings averaged over the video block after the intervention were significantly different between the distancing and the control group ($T^2 = 24.48$, $F = 4.71$, $p < 0.001$). In contrast, before the intervention the mean ratings did not show a significant difference between groups ($T^2 = 6.53$, $F = 1.26$, $p = 0.29$). The within-subject change in average ratings (after minus before intervention) differed significantly between groups($T^2 = 52.66$, $F = 10.14$, $p < 0.001$). Additionally, we observed a significant interaction between time and intervention group ($F(5, 208) = 2.6$, $p = 0.026$).

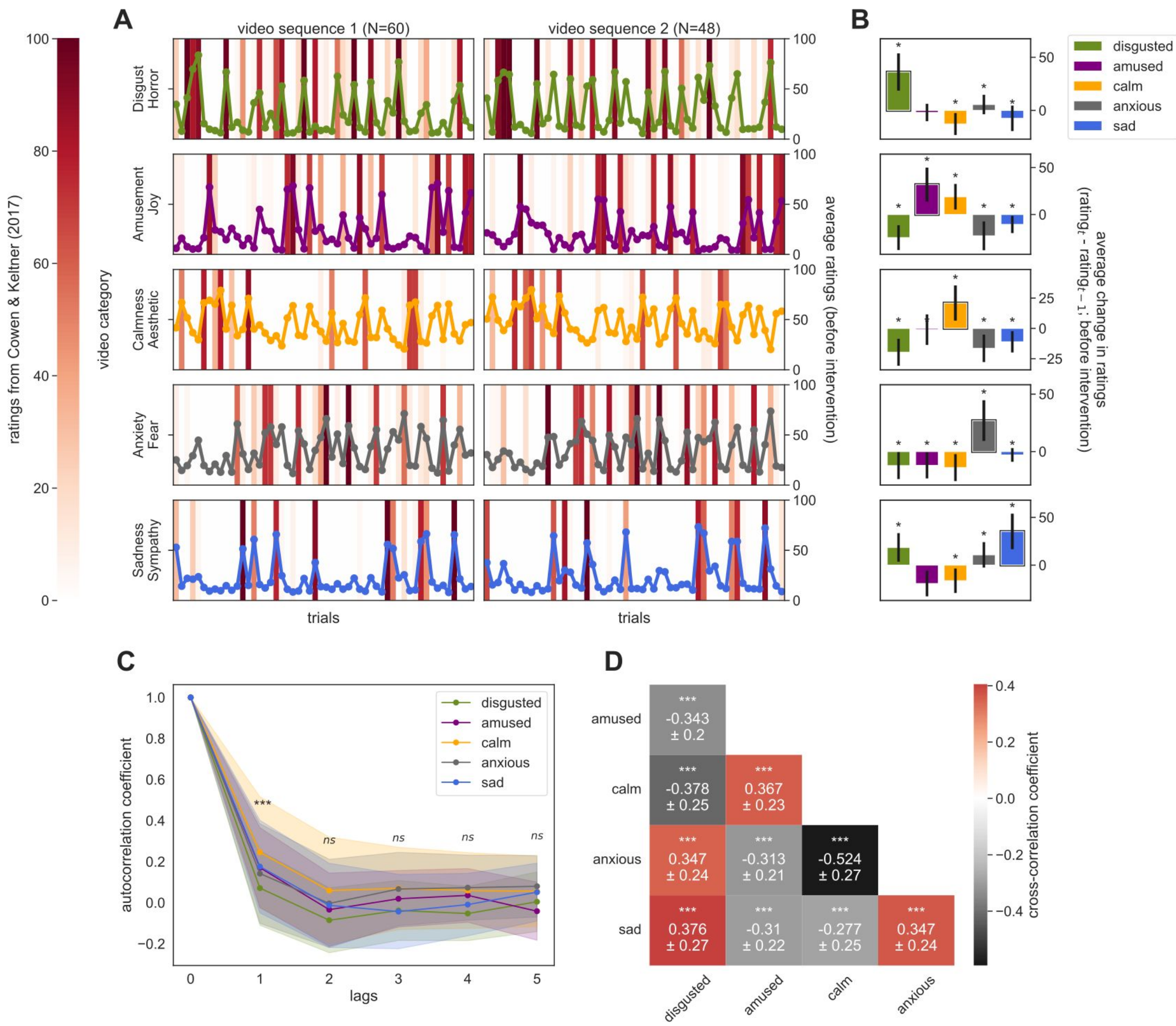


Figure 3

Emotion Ratings

A) The heatmap shows for each emotion eliciting video category the ratings from Cowen and Keltner (2017) averaged over the two emotion categories of interest (left y-axis). The coloured lines with dots report the emotion ratings from our experiment for each emotion after watching a video clip averaged over participants before the intervention occurred for the randomized and matched video sequences separately (right y-axis). **B)** shows the change between the rating (t) after a certain video and the previous rating (t - 1) averaged over participants and all trials, including videos from the same video category. Subplot B has the same emotion categories as subplot A (left label of A). The bar represents the mean of the change in ratings, the black line shows the standard deviation, and the * indicates a significant difference from zero. The black frame shows the dominant emotion for the specific emotion category (the emotion intended to be elicited by watching videos from that category). The unframed bars show that videos from a specific emotion category also affected non-dominant emotions. **C)** shows the autocorrelation coefficient averaged over participants for five lags for each emotion. The line indicates the mean and the shaded area standard deviation over participants. **D)** shows the mean and standard deviation of the cross-correlation coefficients between emotion time-series averaged over participants. Significance *≤ 0.5, **≤ 0.1, ***≤ 0.001, ****≤ 0.0001

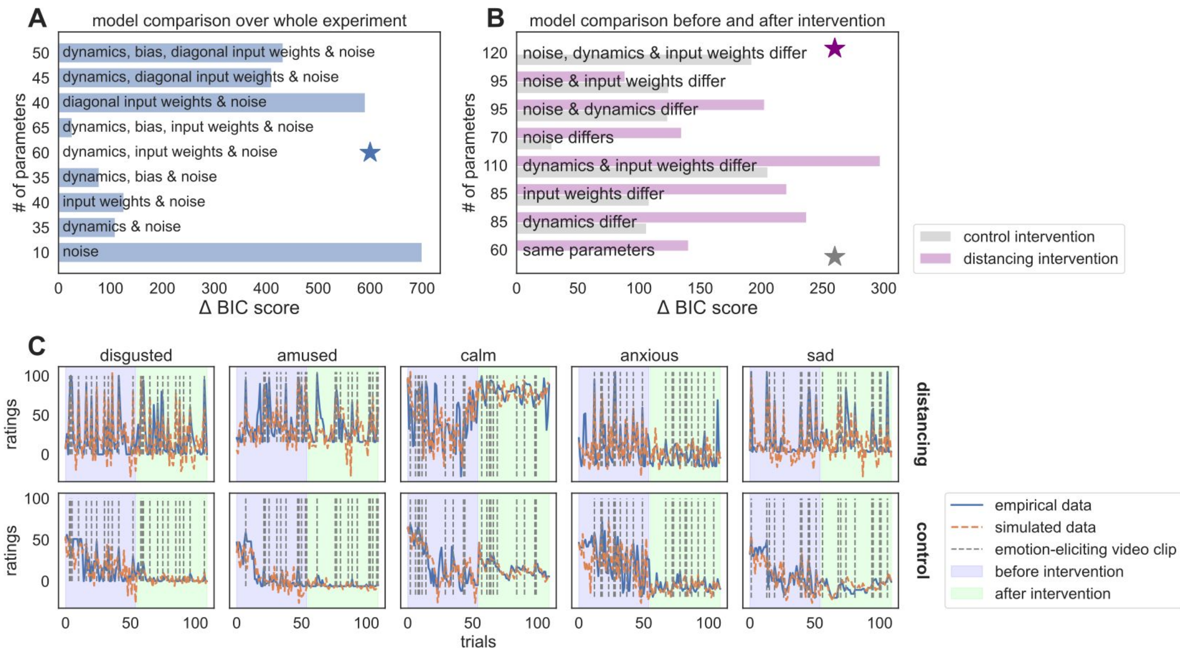


Figure 4

Model Evaluation

A) shows the differences in Bayesian Information Criterion (BIC) scores for all models tested compared to the most parsimonious model (blue star). All models were separately fitted to individuals' emotion rating time-series over the whole experiment. The left y-axis shows the number of free parameters for each model. The most parsimonious model included a dynamics matrix, input weights and diagonal noise covariances for observation and process noise. **B)** shows differences in BIC scores of models, allowing for parameters to change after the intervention. While in the control group, a model in which all parameters stayed the same best explained the data (grey star), in the distancing group dynamics matrix, input weights and noise covariances differed in the most parsimonious model (purple star). **C)** shows empirical (blue) and simulated data (orange) from two randomly selected participants. One of those was allocated to the control intervention and one to the distancing intervention. We simulated data from a linear state space model using the parameter estimates derived from fitting the Kalman Filter to individuals' emotion rating time-series. The vertical grey dashed line indicates that a video was shown at that time-point which stems from the category aiming to elicit that specific emotion. Blue shading indicates the period before, and green shading after the intervention. Data was simulated based on different parameter sets before and after the intervention.

At the group-level, all emotion ratings were significantly reduced after the distancing intervention ($U \in [688,910]$ for all comparisons, all $p \leq 0.001$), except for ratings of calmness which were increased ($U = 1824$, $p = 0.02$; though this does not survive Bonferroni correction $p \leq \frac{0.05}{5} \leq 0.01$). Furthermore, while this pattern was observable in the distancing group ($W \in [68, 308]$ for all comparisons, all $p < 0.001$, before vs after), no changes were detectable in the control group ($W \in [401,561]$ for all comparisons, all $p \geq 0.01$, except for amused $W = 273.0$, $p < 0.001$).

Distancing also affected the temporal variability in emotion ratings (group comparison after intervention: $T^2 = 36.53$, $F = 7.03$, $p < 0.001$). The variances of all emotions were reduced ($U \in [576, 983]$ for all comparisons, all $p \leq 0.004$) in the distancing group compared to the control group and they significantly differed before and after the intervention within the distancing group ($W \in [133, 246]$ for all comparisons, all $p < 0.001$). However, the interaction effect in a MANOVA was not significant (F (5, 208) = 1.72, $p = 0.13$).

Overall, the distancing intervention strongly affected the mean emotions subjects reported and the variability of emotions (cf. full table in Supplementary Materials **Table I.5**).

To examine whether the observed group differences are attributable to a demand effect, we analyzed the time taken by participants to rate their emotions on the sliders. We reasoned that if a demand effect were present, participants would respond more quickly as they would already have decided in advance of the question how to respond. Using a mixed ANOVA with time (before vs after the intervention) and intervention groups as factors, we found evidence of a significant interaction effect between time and group (F (1, 106) = 6.46, $p = 0.01$). However, interestingly, the *control* group demonstrated a decrease in reaction time (before: $M = 12029$, $SD = 2813$ (ms); after: $M = 10964$, $SD = 2713$ (ms); $t = 5.87$, $p < 0.001$), while the distancing group did not show a significant difference in reaction time before and after the intervention (before: $M = 11876$, $SD = 2796$ (ms); after: $M = 11518$, $SD = 2896$ (ms), $t = 1.73$, $p = 0.09$).

3.5 Effects of Distancing on Dynamics of Emotions

Next, we examined whether the intrinsic dynamics or the input weights or both were altered by the distancing intervention (**Fig. 4C**). In principle, the observed effect of distancing on the mean and variance of emotion ratings can be explained either by changing the internal dynamics or by changing the input weights alone (cf. Supplementary Material **Figure G.5**). We hence applied model comparison to examine whether either a change in the dynamics, or in the input weights, or in both was required to capture the data. In the control group, the most parsimonious model (99% of model weight) was the one where the dynamics before and after the intervention stayed the same. That is, there was no evidence for a change in either input weights or dynamics. By contrast, in the distancing group, a model where noise, dynamics, and input weights changed with the intervention provided the most parsimonious account of the data (99% of model weight). Again, data generated from this model was able to capture the observed data sequences accurately (cf. **Fig. 4D**). Overall, this suggests that the distancing intervention changed both the dynamics and the influence of the videos.

We then examined the specific dynamical features that changed in response to the distancing intervention. Four participants had to be excluded as they were outliers in dynamical characteristics (cf. Supplementary Materials E Exclusion). The following analyses were hence based on 104 participants (54 randomized to the distancing intervention).

Distancing altered the input weights (**C** matrix) shown in a group comparison of the matrix norm (after intervention: distancing group $M = 256$, $SD = 218$; control group $M = 400$, $SD = 222$; $U = 1897$, $p < 0.001$) and in **Figure 5B&C**.

Furthermore, a linear dynamical system can be decomposed into eigenmodes - parallel, independent dynamical systems - using an eigendecomposition of the dynamics matrix **A** (cf. 2.3.2 Stability). Distancing altered the composition of the emotional eigenmodes (T^2 = 14.81, F = 2.85, p = 0.019; **Fig. 5D**). This component was also more stable (decayed more slowly) in the distancing group (distancing group M =0.69, SD = 0.21; control group M = 0.52, SD = 0.22; U = 762, p < 0.001; **Fig. 5D**) after the intervention. Hence, when controlling for the emotional input, the distancing intervention had specific effects on how different emotional states persisted and interacted.

3.6 Effects of Distancing on Controllability of Emotions

The dynamics matrix **A** and the input weight matrix **C** jointly determine the extent to which the emotional state can be controlled by external inputs. This can be formally assessed through a measure called controllability, which we turn to next (cf. 2.3.3 Controllability). Controllability formalizes how strong the inputs to the system have to be to move the dynamical system around, i.e. how 'reactive' the dynamical system is to inputs.

The intervention altered controllability overall (group comparison of matrix norm after intervention: distancing group M = 335, SD = 284; control group M = 509, SD = 292; U = 1851, p = 0.001).

Controllability can, however, vary, with the system being more controllable in certain directions than others. This can be examined by studying the eigenspace of the controllability Gramian C, which is based on a combination of dynamics and input matrices, **A** and **C**. The eigenspace corresponding to the dominant eigenvalue of the controllability matrix, describing the most controllable direction, differed between the intervention groups after (T^2 = 24.67, F = 4.74, p < 0.001), but not before (T^2 = 3.69, F = 0.71, p = 0.618), the intervention. A posthoc MANOVA revealed a significant interaction between time and intervention group on the most controllable direction (F (5, 200) = 2.5, p = 0.03). Distancing altered which combination of emotions was most controllable (**Fig. 5F**), with combinations involving more calm (U = 874, p = 0.002) and less sad emotions (U = 1926, p < 0.001) being most controllable. This direction was, overall, less controllable (lower singular value; U = 1844, p = 0.001; **Fig. 5E**) in the distancing group.

3.7 Psychopathological correlates

The control of emotional states is thought to be altered in mental illness. Hence we examined controllability in relation to the three assessed psychological questionnaires, focusing on the self-reported emotion regulation difficulties. All questionnaires showed a good internal consistency ($C_a \in$ [0.89,0.91]). The total scores of the three questionnaires were highly correlated ($r \in$ [0.69,0.75], p < 0.001) and distributions of scores were skewed towards lower values (cf. Supplementary Material **Figure H.6**).

Psychological well-being was significantly related to emotion ratings at baseline (t_0), emotion ratings averaged over the first video block (t_1) and the second video block (t_2). Ratings of disgust, sadness and anxiousness were positively associated with PHQ-9, GAD-7, and DERS-18 total scores ($\beta \in$ [0.18,0.56] for all comparisons, all $p \leq 0.03$; except for GAD-7 and disgust at t_0 and t_2 β < 0.12, p > 0.2). Ratings of calmness decreased with increasing symptoms ($\beta \in$ [-0.18, -0.4] for all comparisons, all $p \leq 0.05$). There was no relationship between amusement and symptoms. However, critically none of the symptom scores interacted with group allocation in predicting change in emotion ratings (all p > 0.05; cf. Supplementary Material **Table I.7**).

Psychopathological symptoms were related to aspects of the dynamics of emotions. Difficulties in distancing as measured by the DERS-18 were related to the most controllable direction in the emotion space. In those participants with high DERS-18 scores, the most controllable direction pointed towards disgust (β = 0.26, p = 0.006), and away from amusement (β = -0.26, p = 0.005) and

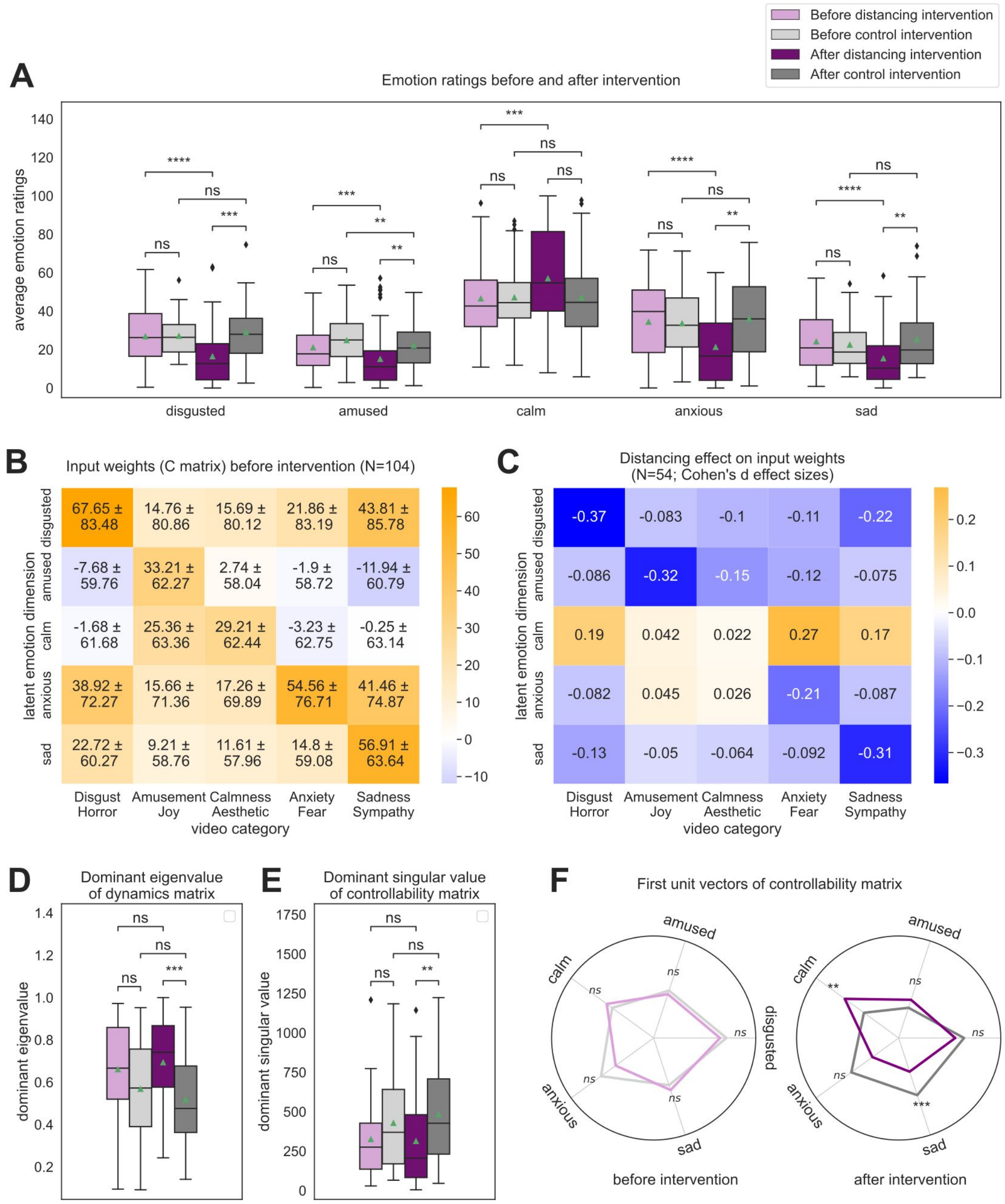


Figure 5

Intervention Effects

A) shows the average ratings separated in before and after the intervention and for both intervention groups. Purple shades refer to the distancing group and grey shades to the control group. The boxes show the quartiles of the ratings, while the whiskers extend to show the rest of the distribution. The horizontal bars in the boxes indicate the median, and the green triangles the mean across participants. **B)** shows mean and standard deviation for the elements of the input weight matrix (**C** matrix) averaged across participants before the intervention occurred. **C)** shows the effect of distancing on the input weight matrix (**C** matrix), which is computed as the mean change (after minus before intervention) divided by its standard deviation for each matrix element only in participants allocated to the distancing intervention. **D)** The boxplot presents the quartiles of the dominant eigenvalues of the dynamics matrix, while the whiskers display the rest of the distribution. **E)** The boxplot illustrates the quartiles of the dominant singular values of the controllability matrix, with the whiskers showing the rest of the distribution. **F)** The polar plots show the unit vector direction of the dominant singular value separated between participants in the distancing (purple shades) and the control (grey shades) group before (left) and after (right) intervention. Significance *≤ 0.05, **≤ 0.01, ***≤ 0.001, ****≤ 0.0001. We report the significance after Bonferroni correction for testing five different emotions.

calmness (β = -0.24, p = 0.011; though this did not survive Bonferroni correction). In other words, self-reported emotion regulation difficulties were related to needing less effort to drive disgust and more effort to steer the emotional experience towards calm and amused. The effect of DERS-18 total score on disgust was even more prominent after the intervention (β = 0.35, p < 0.001).

There was no evidence that the symptoms moderated the effect of distancing (all p > 0.05; cf. Supplementary Material **Table I.8**).

4 Discussion

Psychotherapeutic approaches effectively treat a variety of psychiatric conditions. However, the mechanisms underlying these psychotherapeutic effects remain unclear (Kazdin, 2009). By isolating a specific intervention component, such as emotion regulation, we aim to gain a deeper understanding of the processes involved in this specific treatment effect. Emotion regulation techniques are core components of psychotherapy (McRae and Gross, 2020; Powers and LaBar, 2019; Gross, 2015). To study emotion regulation strategies, it is essential to investigate emotions and consider that they fluctuate in intensity and frequency over time, potentially giving rise to a complex dynamical system. We believe that by examining the emotion dynamics of a particular individual, we can better understand how emotions change and how they respond to different interventions.

Here, we studied the impact of an emotion regulation technique called distancing on the dynamics of emotions over time. We used rich and powerful video stimuli to evoke and alter a complex emotional state in participants. This approach allowed us to achieve three main objectives: first, we established how different emotions influence each other over time in a dynamic system; second, we assessed the relative impact of the video clips on these emotions; and finally, we disentangled the effect of distancing on the stability and controllability of these emotional states.

Importance of external inputs in a dynamical system

Our findings revealed that video clips evoked complex patterns in self-reported emotional experiences, including interrelated emotional trajectories. This highlights the significance of considering multidimensional emotional experiences, their interactions, and temporal dependencies, rather than focusing on a single emotion in isolation (Kendler, 2016; Hitchcock et al., 2022; Durstewitz et al., 2020; Kuppens and Verduyn, 2017; Lange et al., 2022). Computational modeling results suggest that external inputs (video clips) were important in explaining a higher dimensional emotional state. In other words, models that included these inputs provided a better explanation of the self-reported emotion responses. This is in line with recent experimental research demonstrating how unexpected and personally-relevant events are associated with measurable changes in the time course of individuals' emotional responses (Villano et al., 2020; Rutledge et al., 2014; Eldar et al., 2016; Asutay et al., 2022; Lapate and Heller, 2020). Omitting inputs when studying the properties of a dynamical system can lead to inaccurate conclusions as the inputs can mask or alter the apparent dynamics of the system. For instance, Vanhasbroeck et al. (2022) has observed that nonlinearity observed in affective time series in some individuals was the result of external inputs rather than underlying nonlinearity in affect. Hence, to ensure an accurate understanding of the affective system, it is crucial to consider the relationship between affect dynamics and the immediate environment.

Distancing effect on emotional controllability

First, the distancing intervention reliably reduced ratings and variability of both positive and negative emotions but increased ratings of a specific variable, namely feeling calm.

Second, the modeling approach enabled a formal, quantitative assessment of the impact of the distancing intervention on these components. Model comparison showed that the combination of dynamic and controllability signatures changed due to the distancing intervention. Specifically, a brief distancing intervention stabilized intrinsic emotional dynamics and reduced the impact of external stimuli. This finding is significant because static mean differences could be attributed to changes in either dynamics or input sensitivity alone. Interestingly, the intervention affected emotions differently: the controllability of calmness decreased, while sadness increased relative to other emotions. This suggests that some emotions may be more responsive to regulation through distancing.

Emotional controllability and psychopathology

Psychopathology has been associated with deficits in cognitive control (Grahek et al., 2018; Snyder, 2013). The belief that emotions can be controlled to some extent was linked to a decrease in symptoms of anxiety and depression. This connection can be attributed, at least in part, to the fact that individuals with such beliefs tend to employ adaptive strategies for regulating their emotions more frequently (Somerville et al., 2022).

Distancing involves several cognitive control processes, such as taking a step back from a situation, observing it objectively, and cognitively re-framing the experience to focus on positive aspects rather than negative feelings (McRae and Gross, 2020; Ochsner et al., 2004; Dorfel et al., 2014; Staudinger et al., 2009). These processes may include inhibiting pre-potent evaluations, shifting attention away from external stimuli towards the self, and maintaining an intention to detach (McRae and Gross, 2020; Ochsner et al., 2004; Dorfel et al., 2014; Staudinger et al., 2009). Our study demonstrated that the distancing intervention effectively reduced emotional variability and increased feelings of calmness, indicating enhanced emotional control. Furthermore, our modeling showed that the distancing intervention stabilized intrinsic emotional dynamics and reduced the impact of external stimuli. This suggests that distancing can improve emotional stability by enhancing cognitive control. This is consistent with evidence that individuals with high self-control are more successful in regulating emotions (Paschke et al., 2016) and that emotional stability is linked to self-control (Daly et al., 2014; Tangney et al., 2004; Oaten and Cheng, 2006).

An interesting consideration is that cognitive biases may influence emotion regulation ability, thereby contributing to sustained negative affect and reduced levels of positive affect (Joormann and Tanovic, 2015; McRae et al., 2012). For instance, individuals with depression often have difficulty inhibiting negative thoughts or shifting their attention away from negative stimuli. This can lead to a cycle of negative thinking that worsen symptoms (Beck and Haigh, 2014). Our study found that difficulties in emotion regulation were specifically linked to the controllability of emotions such as disgust, amusement, and calmness, indicating that these emotions may be more intrinsically tied to individuals' perceived ability to regulate their emotions (Gross, 2015; Mitchell, 2021). Notably, emotions like amusement and disgust are strongly influenced by external events, suggesting that the emotional impact of external stimuli plays a critical role in the complexity of emotion regulation difficulties in psychopathology. However, contrary to our expectation, we did not find a correlation between symptoms of psychopathology and the efficacy of the distancing intervention.

Future directions

Our investigation confirms that emotional dynamics and their controllability are complex and context-dependent. Future research needs to be examined whether the findings discovered in this study can be applied beyond the realm of video-induced emotions. The key challenge here will be the appropriate, but necessary, characterisation of inputs. Unless inputs are well-known, the true internal dynamics are not identifiable. However, in more naturalistic environments this appears very difficult (Malamud and Huys, 2024).

4.1 Limitations

This study comes with several limitations. First, it is challenging to identify the degree of influence of possible demand effects. We attempted to avoid this influence by providing participants with the sense that distancing does not work for everyone, and we were interested in how it works for them; however, this might not have been enough. On the other hand, the specifics of the effects of the intervention are probably not predicted from simple demand effects.

Second, employing a standard Kalman Filter approach to analyze the time-series of emotion ratings and video inputs, was based on several considerations. i) There are ample tools for the analysis and characterization of Kalman Filters readily available. ii) The Kalman Filter allows for observations to be noisy. This contrasts with typical analyses of EMA and similar timeseries emotion ratings data, which do not allow for noise in the observations. This is important because the noise in ratings influences estimates of parameters as the rating error 'persists' in the modelled future. Nevertheless, one drawback of the Kalman Filter approach we employed was that Gaussian observation noise was assumed, and this is likely to impact the details of the results. However, reconstructed time-series were qualitatively close to the real time-series, and hence we do not believe that the fundamental conclusions here are likely to be affected by this.

Finally, it is possible that eye gaze redirection away from emotionally charged regions in the videos could have acted as an intervening factor in emotion downregulation. Future research could tackle that problem by tracking eye movement.

4.2 Conclusion

In conclusion, we used a novel methodological approach to characterize a key aspect of emotional states, namely how they can be controlled. We found that a brief distancing intervention can effectively regulate emotional experiences, reduce emotional variability and enhance the feeling of calmness. Moreover, distancing leads to qualitatively different changes in the dynamical structure of emotional states. First, it increases the intrinsic emotional stability, and second it reduces the impact of external inputs. Together, these alter the extent to which emotional states are externally controlled. Further computationally detailed characterization of emotional state dynamics and psychotherapeutic interventions may be useful on the path towards understanding differential and specific effects of different psychotherapeutic interventions.

Supplementary Material

A Intervention Text

A.1 Distancing intervention text

For the second part of the study, we would like you to try out an emotion regulation technique called distancing. This technique involves viewing your emotions and thoughts as events passing in your mind rather than getting sucked in by them. We are interested in hearing whether and how well this works for you. It works for some people, but not for all.

What do I have to do? Usually, when an event evokes an emotion, we get sucked in. One way of regulating emotions is to avoid getting sucked in, and instead attempt to stand back and observe the emotion that happens to you as if it was a passing event. To illustrate this, we will walk you through a short mindfulness exercise called "Leaves on a Stream".

Imagine you are resting by the side of a gently flowing stream watching the water flow. Focus on the stream, the sound of the water and other ambiance, the physical sensations, and anything else that comes to mind. Imagine that there are leaves from trees, of all different shapes, sizes, and colors, floating past on the stream and you are just watching the leaves float on the stream. The stream does not stop, it goes on continuously, and the water can easily carry the leaves down/away. Now try to be aware of your emotions and thoughts. When an emotion or thought comes up, imagine you place the thought on one of those leaves and that you are watching the leave - carrying your emotion or thought - float away, disappearing behind a corner or in the distance. Some of the clips you are about to see are likely to elicit emotions. When the emotions start to come, try to notice them without judgment. Emotions will intensify with each video clip. Try to feel them, allow them to come, and then also allow them to go again, like the leaves floating past. Try to treat all your emotions the same, whether comfortable or uncomfortable. The goal is to become aware of your emotions — not to change or improve them. Allow them to come, and then to go again.

A.2 Control intervention text

Before you continue to the second part of the study, we would like to ask you to engage in a relaxation exercise.

What do I have to do? We are going to walk you through a relaxing exercise. Just read the next pages and try to relax.

Imagine you are resting by the side of a gently flowing stream watching the water flow. Focus on the stream, the sound of the water and other ambiance, the physical sensations, and anything else that comes to mind. Imagine that there are leaves from trees, of all different shapes, sizes, and colors, floating past on the stream and you are just watching the leaves float on the stream. The stream does not stop, it goes on continuously, and the water can easily carry the leaves down/away. Now keep thinking of the river and try to relax. Imagine you are standing next to the river, and you are watching the leaves floating by, passing in front of you and then disappearing in the distance. For the next part of video clips, we would like to ask you to keep doing what you have been doing in the first part: watching video clips and reporting your emotions.

B Video Clips

The video clip database referenced in Cowen and Keltner (2017) has been validated and contains 2185 videos (*https://s3-us-west-1.amazonaws.com/emogifs/uncensored.html*) that have been labelled by 853 subjects across 34 emotion categories. Out of this database, we selected video clips with a high rating and low entropy in the five emotion categories of interest (Amusement/Joy, Disgust/Horror, Sadness/Sympathy, Calmness/Aesthetic Adoration, Anxiety/Fear). 20 videos per emotion category were chosen resulting in 50 videos per sequence. It was not feasible to find videos that elicited only the emotion of interest. However, since 10 videos from each category were presented in each sequence, differences were likely to be smoothed out.

Figure B.1

The mean rating (blue bars) and standard deviations (black line) of 20 video clips in each category. Video clips were chosen based on the highest ratings and lowest entropies. A specific emotion-eliciting video category predominantly affected a focused cluster of related emotions.

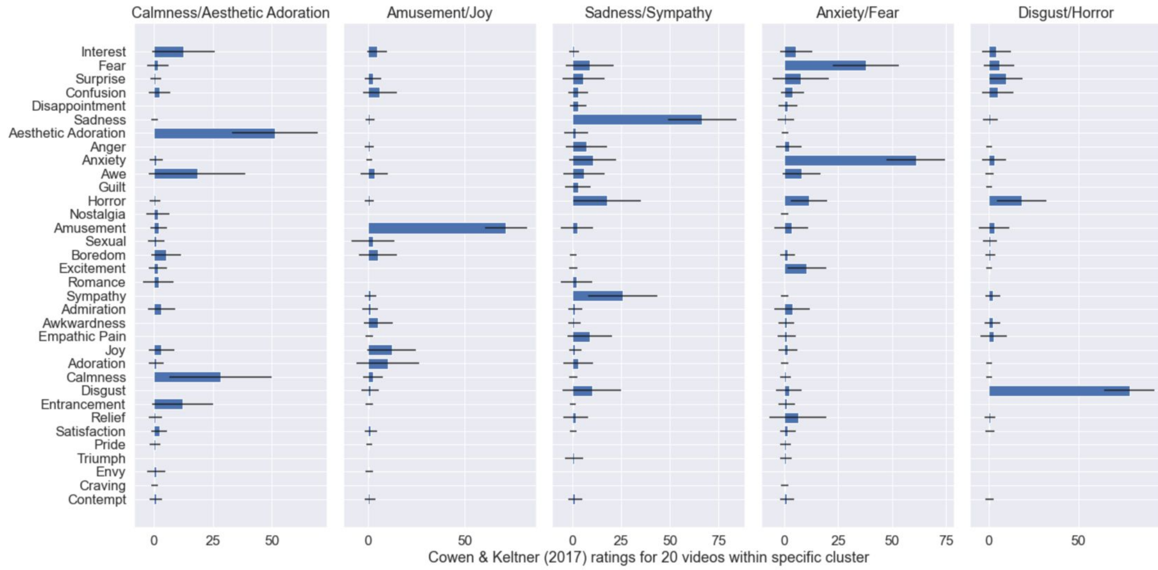
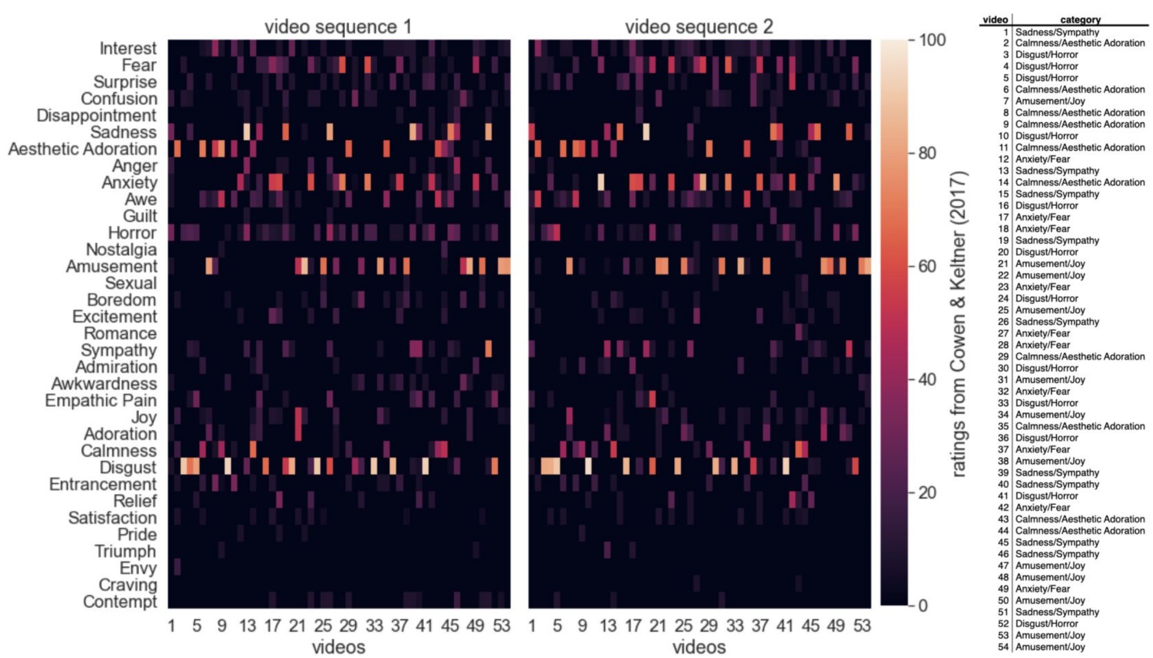


Figure B.2

Heatmap showing the intensity of ratings extracted from Cowen and Keltner (2017) for the chosen video sequences. Video clips elicited the intended emotions in a relatively specific manner. The table located on the right displays the category to which each video belongs.



C Experimental Design

In a simulation study, we utilized a linear KF to generate time-series and determine the appropriate number of trials needed for accurate parameter recovery. We simulated 100 datasets, each containing five-dimensional emotion trajectories and five-dimensional inputs (according to our experimenal setup) for varying numbers of trials (T = [10, 30, 50, 70, 90]). Next, we estimated the parameters for each simulated dataset and computed similarity measures such as correlation and dot-product between the known parameters used for simulation and the estimated parameters from the simulated data.

Our findings showed that with 50 measurement points (**Fig. C.3**), the parameters of interest (i.e. dynamic matrix and input weights) could be recovered almost perfectly. Based on this, we opted to use 50 trials before and after the intervention, which allowed us to fit the model independently to the ratings obtained before and after the intervention while still ensuring accurate recovery of the parameters.

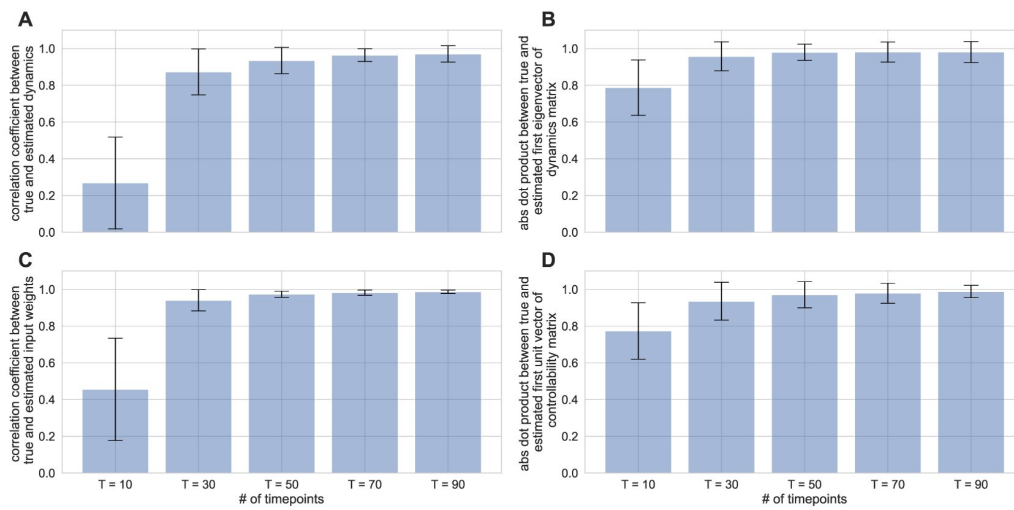


Figure C.3

A) & **B)** show the recoverability of the dynamics matrix based on the correlation between entries of the known and estimated dynamics matrix (A) and the absolute dot product of the known and estimated first eigenvector of the dynamics matrix (B). **C)** demonstrates the recoverability of the input weights by computing the average correlation between entries of the known and estimated input weight matrix. **D)** shows the absolute dot product of the known and estimated first unit vector of the controllability matrix. Blue bars indicate the mean averaged across 100 simulated datasets and the black errorbars indicate the standard deviation.

D Power Analysis

To estimate the sample size, we collected pilot data online (N=40). In the pilot study, 3 participants failed the attention checks leaving 37 participants for the analyses. Two main hypotheses were tested: that 1) the first eigenvector of the dynamics matrix and 2) the first unit vector of the controllability matrix differ between intervention groups after the intervention. The lower effect size across both tests in the pilot study (Hotelling T^2 effect size = 0.81) was used for our power analysis, which suggests that a sample of N = 102 is sufficient to reach 90% power for both hypotheses (G*Power (Faul et al., 2007, 2009); Hotelling T^2 : Two group mean vectors). We added 7 extra participants because we observed an exclusion rate of 7% due to failed attention checks.

E Exclusion

Two participants were excluded from the analysis due to their dominant eigenvalue of the dynamics matrix being greater than 1, indicating an unstable process. Additionally, two other participants were excluded because of outliers in the singular values of the controllability matrix, which resulted from large values in the input weights. Outliers were identified using IQR outlier detection. IQR outlier detection is based on the interquartile range (IQR), which is the difference between the first and third quartiles of a dataset. Outliers are defined as data points that fall outside of the range of the first quartile minus 1.5 times the IQR to the third quartile plus 1.5 times the IQR. For the singular values of the controllability matrix the IQR ranged from -519.81 to 1263.54. Two subjects had values outside that range (-595.63, 1363.61) and hence were excluded.

F Parameter Recovery

We investigated the recoverability of the parameters in our datasets. Initially, we estimated the parameters for every individual. Subsequently, we utilized the derived parameter estimates to generate surrogate mood trajectories for each individual. Afterward, we re-estimated the parameters based on the surrogate time-series. We calculated the Spearman correlation coefficient between the known and re-estimated dynamics matrices (**A**), resp. input weight matrices (**C**), for each individual.

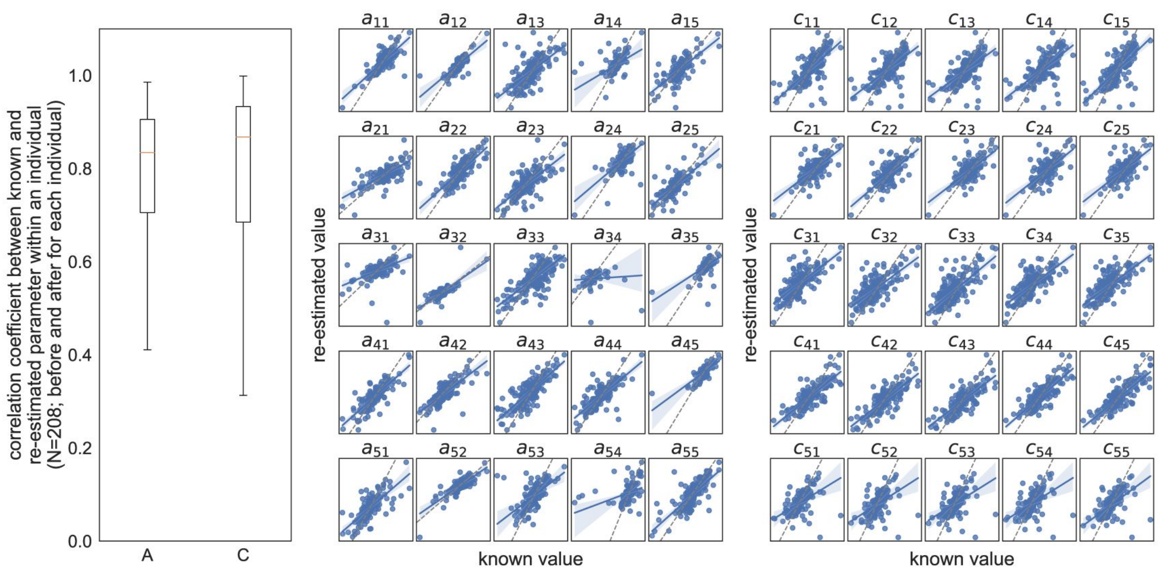


Figure F.4

A) The boxplot illustrates the quartiles of the Spearman correlation averaged over all matrix elements for the dynamic matrix (**A**) and the input weight matrix (**C**). The whiskers showing the rest of the distribution. **B)** shows a scatterplot matrix for the single elements of the known and re-estimated dynamics matrix and **C)** for the input weights. The black line shows a regression line.

G Replication of Distancing Effect in Simulated Data

In order to demonstrate the replicability of the distancing effect in mean emotion ratings, we conducted simulations for each participant using two distinct models. The first model involved allowing changes solely in the dynamics matrix (**A**) before and after the intervention, while keeping the input weight matrix (**C**) constant (**Fig. G.5 A**). The second model, on the other hand, allowed changes exclusively in the input weight matrix (**C**) before and after the intervention, while keeping the dynamics matrix (**A**) unchanged (**Fig. G.5 B**). The mean and variance of simulated ratings obtained from both models showed significant differences between the distancing and control groups after the intervention (**Table G.1**).

		mean ratings			**variance of ratings**		
		T2	Fstats	pvalue	T2	Fstats	pvalue
model 1:	before intervention	4.28	0.82	0.539	16.91	3.23	0.010
A matrix adapted	after intervention	12.16	2.33	0.049	17.87	3.42	0.007
model 2:	before intervention	7.95	1.53	0.189	13.36	2.56	0.032
C matrix adapted	after intervention	15.14	2.91	0.017	20.55	3.95	0.003

Table G.1

Hottelling T^2-test comparing the mean and variance of simulated ratings between the distancing and control intervention group.

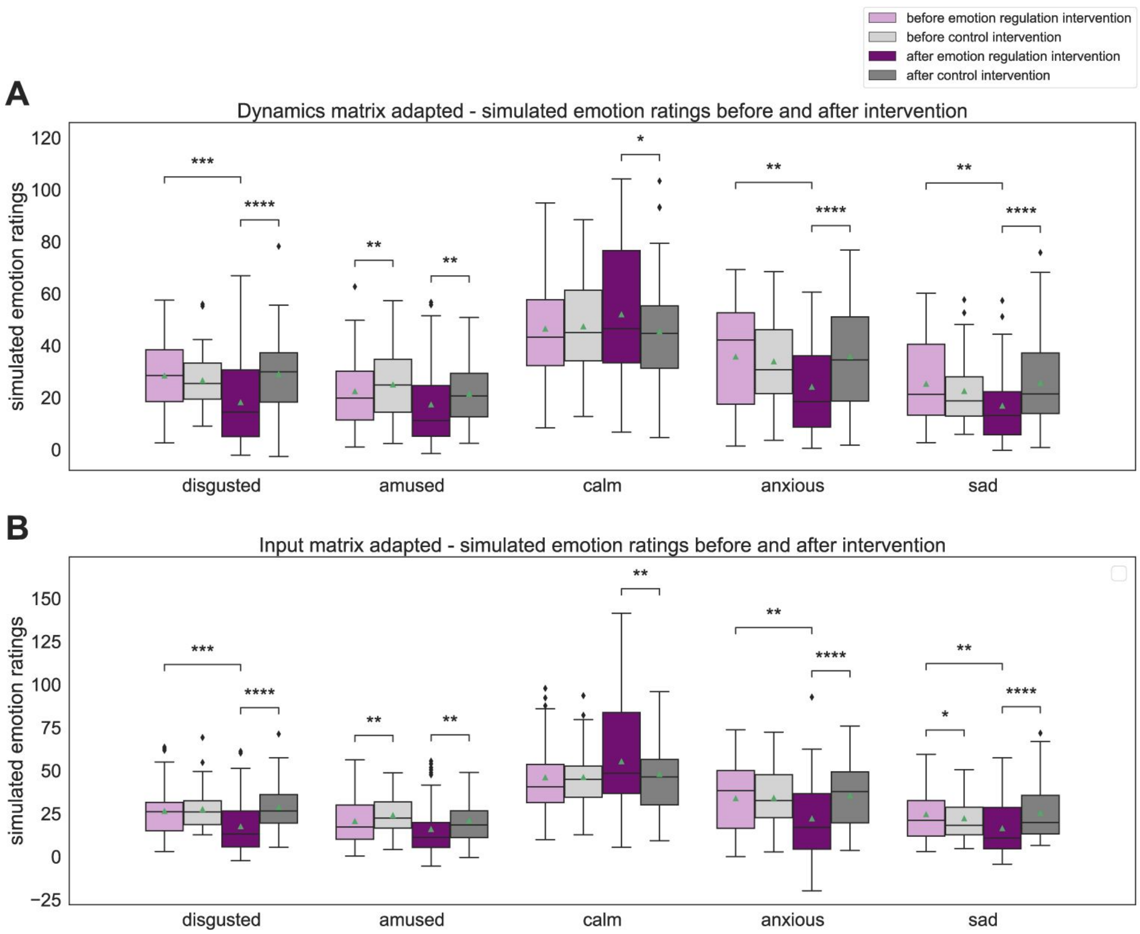


Figure G.5

A) shows that by solely altering **A** before and after the intervention while keeping **C** constant, we could reproduce the difference in mean ratings. **B)** illustrates that altering only the **C** while maintaining the same **A** before and after the intervention also allowed us to replicate the difference in mean ratings.

H Psychopathological Questionnaires

Here, we show the distributions of and the relations between the total sum scores of the three acquired psychological questionnaires measuring symptoms of depression (PHQ-9), generalized anxiety (GAD-7) and self-reported emotion regulation difficulties (DERS-18).

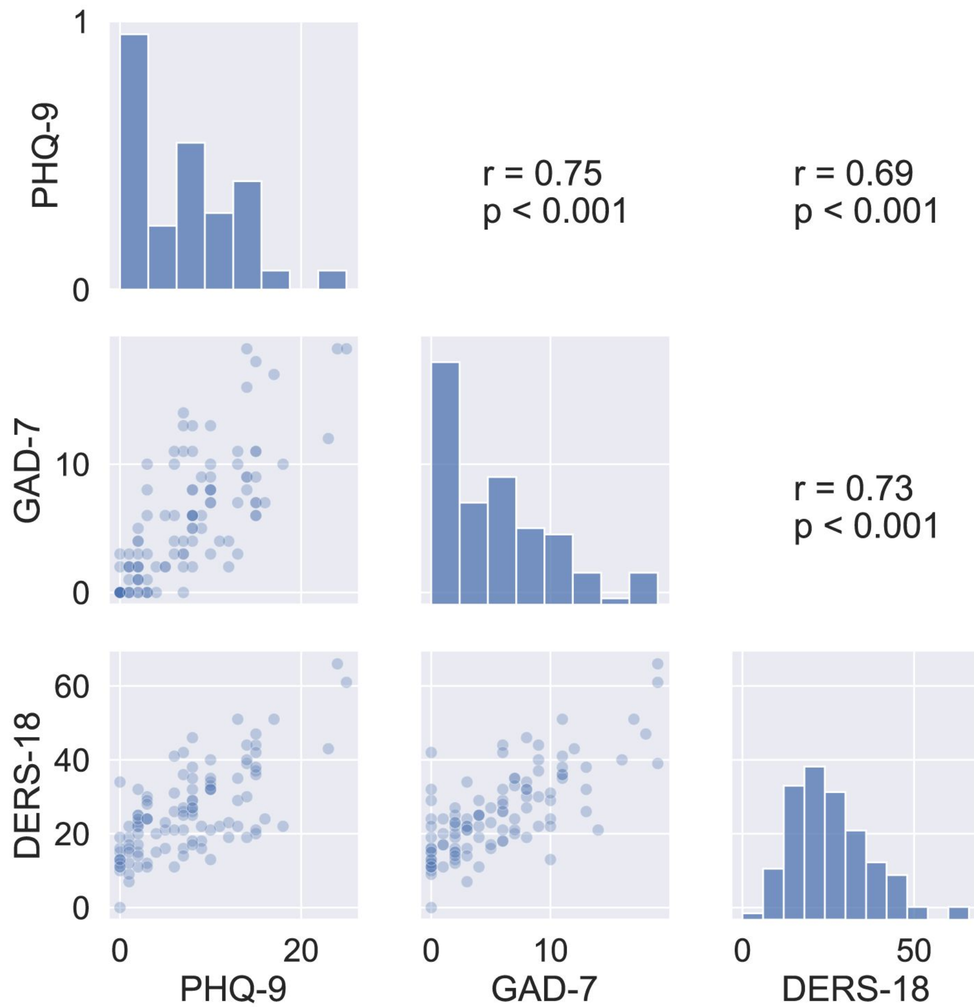


Figure H.6

PHQ-9=Patient Health Questionnaire, 9-item version total score (possible range 0–27). PHQ-9 scores of 5, 10, 15, and 20 represented mild, moderate, moderately severe, and severe depression, respectively. GAD-7=Generalised Anxiety Disorder Assessment, 7-item version total score (possible range 0–21). GAD-7 scores of 5, 10, and 15 are taken as the cut-off points for mild, moderate and severe anxiety, respectively. DERS-18=Difficulties in Emotion Regulation Scale, 18-item version total score (possible range 0–72).

I Additional Tables

video category	dominant emotion (M±SD)	non-dominant emotion (M±SD)	t-test	statistics	pvalue	t-test	statistics	pvalue
Disgust/Horror:	36.09 ± 38.66	NaN	disgusted>disgusted	NaN	NaN	disgusted≠0	21.39	<0.001
Disgust/Horror:	36.09 ± 38.66	-1.94 ± 22.99	disgusted>amused	20.42	<0.001	amused≠0	-2.46	0.016
Disgust/Horror:	36.09 ± 38.66	-12.83 ± 28.06	disgusted>calm	24.97	<0.001	calm≠0	-12.88	<0.001
Disgust/Horror:	36.09 ± 38.66	5.54 ± 29.17	disgusted>anxious	16.04	<0.001	anxious≠0	6.27	<0.001
Disgust/Horror:	36.09 ± 38.66	-7.46 ± 34.43	disgusted>sad	21.27	<0.001	sad≠0	-6.44	<0.001
Amusement/Joy:	31.84 ± 36.0	-24.58 ± 35.07	amused>disgusted	26.18	<0.001	disgusted≠0	-19.28	<0.001
Amusement/Joy:	31.84 ± 36.0	NaN	amused>amused	NaN	NaN	amused≠0	18.32	<0.001
Amusement/Joy:	31.84 ± 36.0	18.92 ± 27.77	amused>calm	5.93	<0.001	calm≠0	14.38	<0.001
Amusement/Joy:	31.84 ± 36.0	-22.69 ± 31.7	amused>anxious	23.86	<0.001	anxious≠0	-15.28	<0.001
Amusement/Joy:	31.84 ± 36.0	-10.56 ± 24.1	amused>sad	21.73	<0.001	sad≠0	-11.89	<0.001
Calmness/Aesthetic Adoration:	20.93 ± 31.33	-19.68 ± 32.69	calm>disgusted	23.06	<0.001	disgusted≠0	-18.25	<0.001
Calmness/Aesthetic Adoration:	20.93 ± 31.33	-1.04 ± 27.45	calm>amused	11.88	<0.001	amused≠0	-0.86	0.393
Calmness/Aesthetic Adoration:	20.93 ± 31.33	NaN	calm>calm	NaN	NaN	calm≠0	15.03	<0.001
Calmness/Aesthetic Adoration:	20.93 ± 31.33	-16.48 ± 28.9	calm>anxious	21.11	<0.001	anxious≠0	-15.03	<0.001
Calmness/Aesthetic Adoration:	20.93 ± 31.33	-11.09 ± 25.53	calm>sad	19.64	<0.001	sad≠0	-13.07	<0.001
Anxiety/Fear:	26.96 ± 33.65	-12.24 ± 34.58	anxious>disgusted	19.15	<0.001	disgusted≠0	-10.81	<0.001
Anxiety/Fear:	26.96 ± 33.65	-12.05 ± 31.58	anxious>amused	19.23	<0.001	amused≠0	-10.97	<0.001
Anxiety/Fear:	26.96 ± 33.65	-13.98 ± 26.55	anxious>calm	20.0	<0.001	calm≠0	-12.34	<0.001
Anxiety/Fear:	26.96 ± 33.65	NaN	anxious>anxious	NaN	NaN	anxious≠0	15.81	<0.001
Anxiety/Fear:	26.96 ± 33.65	-2.94 ± 24.01	anxious>sad	16.61	<0.001	sad≠0	-5.1	<0.001
Sadness/Sympathy:	35.27 ± 39.77	18.5 ± 36.78	sad>disgusted	7.31	<0.001	disgusted≠0	12.79	<0.001
Sadness/Sympathy:	35.27 ± 39.77	-19.32 ± 30.51	sad>amused	24.82	<0.001	amused≠0	-14.97	<0.001
Sadness/Sympathy:	35.27 ± 39.77	-16.38 ± 29.05	sad>calm	23.82	<0.001	calm≠0	-13.25	<0.001
Sadness/Sympathy:	35.27 ± 39.77	10.74 ± 33.06	sad>anxious	11.16	<0.001	anxious≠0	8.33	<0.001
Sadness/Sympathy:	35.27 ± 39.77	NaN	sad>sad	NaN	NaN	sad≠0	19.8	<0.001

Table I.2

The change of emotion ratings from t - 1 to t (where t indicates the rating time after the video from a specific video category was shown) was greater for the video's target emotion than other emotions, but all videos have broad, complex effects. One-sided two-sample t-tests were conducted to test whether the dominant emotion was higher than non-dominant emotions and two-sided one-sample t-tests were performed to test whether the dominant emotion was different from zero.

Table I.3

Mean (M) and standard deviation (SD) of the autocorrelation coefficients of emotion time series averaged over participants and their statistical difference from zero is reported.

		disgusted				amused				calm				anxious				sad			
		M	SD	statistic	pvalue	M	SD	statistic	pvalue	M	SD	statistic	pvalue	M	SD	statistic	pvalue	M	SD	statistic	pvalue
lags	1	0.07	0.18	4.05	<0.001	0.17	0.19	9.05	<0.001	0.25	0.27	9.39	<0.001	0.14	0.24	6.04	<0.001	0.18	0.23	8.05	<0.001
	2	-0.09	0.16	-5.58	<0.001	-0.03	0.18	-1.96	0.052	0.06	0.26	2.34	0.021	-0.00	0.21	-0.17	0.865	-0.01	0.21	-0.66	0.514
	3	-0.04	0.15	-2.69	0.008	0.02	0.14	1.43	0.154	0.07	0.20	3.60	<0.001	0.07	0.18	3.87	<0.001	-0.04	0.18	-2.46	0.015
	4	-0.05	0.13	-4.12	<0.001	0.04	0.13	2.82	0.006	0.06	0.18	3.33	0.001	0.07	0.16	4.78	<0.001	-0.01	0.15	-0.62	0.534
	5	0.00	0.15	0.33	0.74	-0.04	0.14	-3.02	0.003	0.06	0.17	3.34	0.001	0.08	0.15	5.52	<0.001	0.05	0.14	3.76	<0.001

Table I.4

This table reports mean (M) and standard deviation (SD) of the cross-correlation coefficients between emotion time series averaged over participants and their statistical difference from zero.

	M	SD	statistic	pvalue
corr(amused, disgusted)	-0.34	0.20	-17.94	<0.001
corr(calm, disgusted)	-0.38	0.25	-15.76	<0.001
corr(calm, amused)	0.37	0.23	16.20	<0.001
corr(anxious, disgusted)	0.35	0.24	15.23	<0.001
corr(anxious, amused)	-0.31	0.21	-15.50	<0.001
corr(anxious, calm)	-0.52	0.27	-19.81	<0.001
corr(sad, disgusted)	0.38	0.27	14.55	<0.001
corr(sad, amused)	-0.31	0.22	-14.45	<0.001
corr(sad, calm)	-0.28	0.25	-11.46	<0.001
corr(sad, anxious)	0.35	0.24	14.97	<0.001

Table I.5

This table contains group comparisons before and after the intervention and before vs after comparison within group for summary statistics (mean and variance) of emotion ratings, v_1 and v_2 refer to the specific statistic across a subgroup depending on the type of comparison. When comparing intervention groups before (t = 0) and after the intervention (t = 1), v_1 indicates mean (M) and standard deviation (SD) of the control and v_2 of the distancing group. When comparing before vs after the intervention within the control (g = 0) or the distancing (g = 1) group, v_1 indicates M and SD before and v_2 after the intervention happened. For intervention group comparisons, we performed two-sample Mann Whitney U tests, whereas for before and after comparison we used one-sample Wilcoxon signed rank tests.

		disgusted				**amused**				**calm**				**anxious**				**sad**			
		$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue
mean	group comparison $t = 0$	27±10	27±15	1514.5	0.71	25±11	21±13	1738.5	0.08	47±18	47±20	1497.0	0.791	34±16	34±20	1422.0	0.849	22±12	24±16	1439.0	0.931
	group comparison $t = 1$	29±14	16±15	2219.0	< 0.001	22±13	15±16	1997.0	< 0.001	46±22	58±26	1083.5	0.023	36±20	21±18	2091.0	< 0.001	25±16	15±14	2104.5	< 0.001
	before vs after $g = 0$	27±10	29±14	525.5	0.197	25±11	22±13	273.0	< 0.001	47±18	46±22	560.5	0.337	34±16	36±20	471.0	0.072	22±12	25±16	401.0	0.014
	before vs after $g = 1$	27±15	16±15	152.0	< 0.001	21±13	15±16	308.0	< 0.001	47±20	58±26	279.0	< 0.001	34±20	21±18	68.0	< 0.001	24±16	15±14	109.5	< 0.001
variance	group comparison at $t = 0$	1041±409	888±549	1705.0	0.122	804±422	633±399	1787.0	0.04	673±435	660±475	1502.0	0.768	778±511	654±529	1682.0	0.161	747±369	632±467	1739.0	0.079
	group comparison $t = 1$	992±517	472±451	2255.0	< 0.001	703±434	349±317	2164.0	< 0.001	564±478	331±395	1924.0	0.004	715±569	330±377	2098.0	< 0.001	768±461	335±395	2331.0	< 0.001
	before vs after $g = 0$	1041±409	992±517	616.0	0.66	804±422	703±434	345.0	0.003	673±435	564±478	323.0	0.001	778±511	715±569	566.0	0.363	747±369	768±461	623.0	0.708
	before vs after $g = 1$	888±549	472±451	147.0	< 0.001	633±399	349±317	246.0	< 0.001	660±475	331±395	133.0	< 0.001	654±529	330±377	187.0	< 0.001	632±467	335±395	201.0	< 0.001

Table I.6

This table contains group comparisons before and after the intervention and before vs after comparison within group for the single first emotion loadings on the dynamics and the controllability matrix, v_1 and v_2 refer to the specific statistic across a subgroup depending on the type of comparison. When comparing intervention groups before (t = 0) and after the intervention (t = 1), v_1 indicates mean (M) and standard deviation (SD) of the control and v_2 of the distancing group. When comparing before vs after the intervention within the control (g = 0) or the distancing (g = 1) group, v_1 indicates M and SD before and v_2 after the intervention happened. For intervention group comparisons, we performed two-sample Mann Whitney U tests, whereas for before and after comparison we used one-sample Wilcoxon signed rank tests.

		disgusted				amused				calm				anxious				sad			
		$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue	$v1$ (M±SD)	$v2$ (M±SD)	statistics	pvalue
1st eigenvector of dynamics	group comparison at$t = 0$	0.34±0.22	0.36±0.22	1313.0	0.812	0.34±0.21	0.29±0.23	1632.0	0.067	0.39±0.26	0.47±0.27	1136.0	0.165	0.43±0.2	0.38±0.25	1513.0	0.29	0.34±0.19	0.29±0.23	1569.0	0.155
	group comparison $t = 1$	0.35±0.19	0.34±0.25	1422.0	0.642	0.33±0.24	0.26±0.23	1633.0	0.066	0.41±0.23	0.54±0.25	1006.0	0.025	0.38±0.24	0.32±0.26	1575.0	0.144	0.34±0.22	0.26±0.23	1704.0	0.021
	before vs after $g = 0$	0.34±0.22	0.35±0.19	610.0	0.791	0.34±0.21	0.33±0.24	603.0	0.739	0.39±0.26	0.41±0.23	590.0	0.647	0.43±0.2	0.38±0.24	500.0	0.184	0.34±0.19	0.34±0.22	624.0	0.896
	before vs after $g = 1$	0.36±0.22	0.34±0.25	701.0	0.721	0.29±0.23	0.26±0.23	618.0	0.284	0.47±0.27	0.54±0.25	590.0	0.189	0.38±0.25	0.32±0.26	592.0	0.195	0.29±0.23	0.26±0.23	624.0	0.308
1st unit vector of controllability	group comparison at $t = 0$	0.48±0.24	0.47±0.23	1371.0	0.894	0.36±0.21	0.36±0.2	1358.0	0.961	0.37±0.2	0.41±0.22	1234.0	0.452	0.41±0.2	0.34±0.23	1593.0	0.115	0.34±0.18	0.37±0.2	1269.0	0.6
	group comparison $t = 1$	0.49±0.21	0.41±0.24	1588.0	0.122	0.27±0.21	0.31±0.24	1252.0	0.526	0.3±0.2	0.47±0.29	874.0	0.002	0.39±0.23	0.31±0.26	1618.0	0.082	0.46±0.22	0.29±0.24	1926.0	<0.001
	before vs after $g = 0$	0.48±0.24	0.49±0.21	632.0	0.958	0.36±0.21	0.27±0.21	398.0	0.021	0.37±0.2	0.3±0.2	415.0	0.032	0.41±0.2	0.39±0.23	535.0	0.322	0.34±0.18	0.46±0.22	334.0	0.003
	before vs after $g = 1$	0.47±0.23	0.41±0.24	580.0	0.162	0.36±0.2	0.31±0.24	616.0	0.276	0.41±0.22	0.47±0.29	586.0	0.178	0.34±0.23	0.31±0.26	655.0	0.451	0.37±0.2	0.29±0.24	498.0	0.035

Table I.7

This table reports the outcomes of GLMs used to deduce connections between symptoms (PHQ-9, GAD-7, and DERS-18 total scores) and emotion ratings at baseline (to), as well as emotion ratings averaged (M) and variation (VAR) over the first video block (t_1) and the second video block (t_2). We ran separate GLMs to infer i) the associations between emotion summary statistics (DV) and symptoms (IV) controlling for the intervention group, and ii) an interaction effect between symptoms (IV) and intervention group. All variables are z-scored, except for the group variable which is coded 0 for the control group and 1 for the distancing group. Bonferroni correction: $p \leq \frac{0.05}{3*2*5}$ = 0.002; corrected for number of emotions, time-points (before and after the intervention), and number of questionnaires.

		disgusted				amused				calm				anxious				sad			
formula	IV	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]
ratings(t_0)~phq	phq	0.312	0.001	0.131	0.493	0.056	0.566	-0.134	0.246	-0.467	<0.001	-0.635	-0.298	0.521	<0.001	0.358	0.683	0.456	<0.001	0.287	0.626
M(t_1)~phq	phq	0.311	0.001	0.130	0.492	0.106	0.272	-0.083	0.295	-0.184	0.054	-0.371	0.003	0.336	<0.001	0.157	0.515	0.357	<0.001	0.179	0.535
M(t_2)~phq+group	phq	0.184	0.035	0.013	0.354	0.074	0.434	-0.112	0.260	-0.276	0.002	-0.455	-0.098	0.253	0.004	0.083	0.424	0.264	0.003	0.090	0.438
M(t_2)~phq+group	group	-0.867	< 0.001	-1.209	-0.526	-0.464	0.015	-0.837	-0.091	0.500	0.006	0.142	0.858	-0.798	<0.001	-1.140	-0.457	-0.690	<0.001	-1.038	-0.341
M(t_2)~phq*group	phq:group	-0.117	0.508	-0.462	0.229	-0.150	0.435	-0.527	0.227	0.180	0.328	-0.181	0.542	-0.198	0.26	-0.542	0.147	-0.131	0.467	-0.484	0.222
VAR(t_1)~phq	phq	-0.090	0.354	-0.279	0.100	-0.146	0.127	-0.335	0.042	-0.256	0.006	-0.440	-0.072	-0.139	0.148	-0.328	0.049	-0.186	0.051	-0.373	0.001
VAR(t_2)~phq+group	phq	0.034	0.692	-0.135	0.203	0.066	0.451	-0.107	0.240	-0.067	0.48	-0.252	0.118	-0.064	0.48	-0.241	0.114	-0.058	0.509	-0.228	0.113
VAR(t_2)~phq+group	group	-0.948	<0.001	-1.287	-0.609	-0.860	<0.001	-1.207	-0.513	-0.494	0.009	-0.864	-0.123	-0.737	<0.001	-1.092	-0.381	-0.896	<0.001	-1.239	-0.555
VAR(t_2)~phq*group	phq:group	-0.054	0.758	-0.397	0.289	-0.266	0.134	-0.614	0.082	0.052	0.785	-0.324	0.428	-0.232	0.205	-0.589	0.126	-0.131	0.457	-0.477	0.215
ratings(t_0)~gad	gad	0.117	0.224	-0.072	0.306	-0.006	0.951	-0.196	0.184	-0.405	<0.001	-0.579	-0.231	0.561	<0.001	0.403	0.718	0.349	<0.001	0.170	0.527
M(t_1)~gad	gad	0.288	0.002	0.105	0.470	0.048	0.623	-0.142	0.238	-0.301	0.001	-0.483	-0.120	0.447	<0.001	0.277	0.618	0.325	<0.001	0.145	0.505
M(t_2)~gad+group	gad	0.112	0.201	-0.060	0.285	-0.007	0.941	-0.194	0.179	-0.214	0.021	-0.396	-0.032	0.292	0.001	0.124	0.460	0.225	0.012	0.050	0.401
M(t_2)~gad+group	group	-0.832	<0.001	-1.177	-0.487	-0.454	0.017	-0.828	-0.081	0.443	0.017	0.079	0.807	-0.738	<0.001	-1.074	-0.401	-0.633	<0.001	-0.985	-0.281
M(t_2)~gad*group	gad:group	0.315	0.07	-0.026	0.657	0.123	0.519	-0.251	0.497	-0.082	0.661	-0.447	0.283	0.230	0.178	-0.105	0.565	0.212	0.238	-0.140	0.563
VAR(t_1)~gad	gad	0.101	0.295	-0.088	0.291	-0.036	0.707	-0.227	0.154	-0.117	0.225	-0.306	0.072	0.028	0.775	-0.163	0.218	-0.008	0.931	-0.199	0.182
VAR(t_2)~gad+group	gad	0.084	0.329	-0.084	0.252	0.061	0.487	-0.112	0.234	-0.026	0.784	-0.211	0.159	-0.006	0.948	-0.184	0.172	-0.004	0.966	-0.175	0.167
VAR(t_2)~gad+group	group	-0.936	<0.001	-1.273	-0.599	-0.845	<0.001	-1.192	-0.499	-0.505	0.008	-0.876	-0.134	-0.746	<0.001	-1.102	-0.390	-0.905	<0.001	-1.247	-0.563
VAR(t_2)~gad*group	gad:group	0.140	0.416	-0.197	0.477	0.247	0.16	-0.097	0.592	-0.108	0.57	-0.480	0.264	0.298	0.098	-0.055	0.650	0.177	0.311	-0.165	0.518
ratings(t_0)~ders	ders	0.203	0.033	0.016	0.389	-0.015	0.877	-0.205	0.175	-0.387	<0.001	-0.563	-0.212	0.481	<0.001	0.314	0.648	0.408	<0.001	0.234	0.582
M(t_1)~ders	ders	0.379	<0.001	0.203	0.555	0.060	0.535	-0.130	0.250	-0.396	<0.001	-0.570	-0.221	0.458	<0.001	0.288	0.627	0.388	<0.001	0.213	0.563
M(t_2)~ders+group	ders	0.232	0.007	0.065	0.400	0.050	0.598	-0.136	0.236	-0.315	<0.001	-0.491	-0.139	0.305	<0.001	0.138	0.472	0.301	0.001	0.129	0.472
M(t_2)~ders+group	group	-0.831	<0.001	-1.167	-0.495	-0.451	0.018	-0.824	-0.079	0.446	0.013	0.093	0.799	-0.748	<0.001	-1.083	-0.414	-0.638	<0.001	-0.982	-0.295
M(t_2)~ders*group	ders:group	0.288	0.089	-0.044	0.621	0.236	0.214	-0.136	0.607	-0.215	0.23	-0.567	0.136	0.257	0.129	-0.075	0.589	0.176	0.315	-0.167	0.519
VAR(t_1)~ders	ders	0.126	0.193	-0.063	0.314	0.016	0.869	-0.174	0.206	-0.076	0.431	-0.266	0.114	0.076	0.431	-0.114	0.266	0.001	0.993	-0.189	0.191
VAR(t_2)~ders+group	ders	0.120	0.158	-0.047	0.288	0.115	0.19	-0.057	0.287	-0.067	0.474	-0.252	0.117	0.012	0.896	-0.166	0.189	0.027	0.757	-0.144	0.198
VAR(t_2)~ders+group	group	-0.937	<0.001	-1.272	-0.602	-0.845	<0.001	-1.189	-0.501	-0.506	0.007	-0.876	-0.136	-0.745	<0.001	-1.101	-0.389	-0.903	<0.001	-1.245	-0.561
VAR(t_2)~ders*group	ders:group	0.177	0.3	-0.158	0.512	0.300	0.084	-0.040	0.641	0.030	0.876	-0.342	0.401	0.308	0.087	-0.045	0.660	0.224	0.197	-0.116	0.564

Table I.8

This table reports links between single first loadings derived from the dynamics and the controllability matrix and the DERS-18 total score. We ran separate GLMs to infer i) the associations between first eigen-/singular value loadings (DV) and symptoms (IV) controlling for the intervention group, and ii) an interaction effect between symptoms (IV) and intervention group. All variables are z-scored, except for the group variable which is coded 0 for the control group and 1 for the distancing group. Bonferroni correction: $p \leq \frac{0.05}{5} = 0.01$.

		disgusted				amused				calm				anxious				sad			
formula	IV	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]
convec(t_1)~ders	ders	0.260	0.006	0.073	0.447	-0.264	0.005	-0.451	-0.078	-0.243	0.011	-0.430	-0.055	0.079	0.423	-0.114	0.272	0.148	0.13	-0.044	0.339
convec(t_2)~ders+group	group	-0.323	0.079	-0.683	0.037	0.154	0.437	-0.234	0.542	0.662	< 0.001	0.300	1.024	-0.302	0.124	-0.687	0.083	-0.693	< 0.001	-1.054	-0.331
convec(t_2)~ders+group	ders	0.347	< 0.001	0.168	0.527	-0.073	0.461	-0.266	0.121	-0.175	0.057	-0.355	0.005	-0.067	0.494	-0.259	0.125	0.152	0.099	-0.028	0.331
convec(t_2)~ders*group	ders:group	-0.034	0.856	-0.395	0.328	0.197	0.32	-0.191	0.584	-0.139	0.451	-0.501	0.223	0.328	0.092	-0.053	0.709	0.034	0.854	-0.328	0.396
stabvec(t_1)~ders	ders	-0.086	0.379	-0.279	0.106	-0.099	0.313	-0.291	0.093	-0.048	0.622	-0.242	0.145	0.228	0.018	0.039	0.416	0.084	0.395	-0.109	0.276
stabvec(t_2)~ders+group	group	-0.024	0.906	-0.413	0.366	-0.314	0.111	-0.699	0.072	0.515	0.007	0.140	0.890	-0.240	0.224	-0.628	0.147	-0.373	0.05	-0.746	0.001
stabvec(t_2)~ders+group	ders	-0.046	0.642	-0.240	0.148	0.048	0.624	-0.144	0.240	-0.110	0.249	-0.296	0.077	0.020	0.842	-0.173	0.213	0.224	0.018	0.038	0.410
stabvec(t_2)~ders*group	ders:group	0.074	0.712	-0.317	0.464	0.162	0.41	-0.223	0.547	-0.014	0.942	-0.390	0.362	0.190	0.335	-0.197	0.577	-0.064	0.738	-0.438	0.310

Table I.9

This table reports the relationships between the first eigenvalue of the dynamics and the controllability matrix and the DERS-18 total score. We ran separate GLMs to infer i) the associations between first eigen-/singular values (DV) and symptoms (IV) controlling for the intervention group, and ii) an interaction effect between symptoms (IV) and intervention group. All variables are z-scored, except for the group variable which is coded 0 for the control group and 1 for the distancing group.

		controllability				stability			
formula	IV	coef	$P>\|z\|$	[0.025	0.975]	coef	$P>\|z\|$	[0.025	0.975]
val(t_1)~ders	ders	0.046	0.639	-0.147	0.239	-0.005	0.957	-0.199	0.188
val(t_2)~ders+group	group	-0.562	0.003	-0.935	-0.189	0.756	<0.001	0.396	1.116
val(t_2)~ders+group	ders	-0.082	0.384	-0.268	0.103	0.082	0.368	-0.097	0.262
val(t_2)~ders*group	ders:group	0.210	0.269	-0.162	0.582	-0.085	0.646	-0.445	0.276

Data and Code Sharing Statement

Fully anonymised data and code for data analysis of this study is available from a Github repository (*https://github.com/huyslab/emotioncon_public*).

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Additional information

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Ethical Approvals

The UCL research ethics committee approved the study procedures (REC No 21029/001). The participants in the study provided electronic consent to participate in the research and to allow for the publication of the study.

Author Contributions

QJMH and JM collaborated on the study design. JM developed the methodology with guidance from QJMH, and was responsible for conducting the study and analyzing the data under the supervision of QJMH. JM initially drafted the manuscript, which was subsequently revised by QJMH.

References

Asutay E., Genevsky A., Hamilton J. P., Vastfjall D. 2022) **Affective context and its uncertainty drive momentary affective experience** *Emotion* US: American Psychological Association **22**:1336–1346

Beck A. T., Haigh E. A. P. 2014) **Advances in Cognitive Theory and Therapy: The Generic Cognitive Model** *Annual Review of Clinical Psychology* Annual Reviews **10**:1–24

Berking M., Ebert D., Cuijpers P., Hofmann S. G. 2013) **Emotion regulation skills training enhances the efficacy of inpatient cognitive behavioral therapy for major depressive disorder: a randomized controlled trial** *Psychotherapy and Psychosomatics* **82**:234–245

Boemo T., Nieto I., Vazquez C., Sanchez-Lopez A. 2022) **Relations between emotion regulation strategies and affect in daily life: A systematic review and meta-analysis of studies using ecological momentary assessments** *Neuroscience & Biobehavioral Reviews* **139**:104747

Borsboom D., Cramer A. O. 2013) **Network Analysis: An Integrative Approach to the Structure of Psychopathology** *Annual Review of Clinical Psychology* **9**:91–121 https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom D., Deserno M. K., Rhemtulla M., Epskamp S., Fried E. I., McNally R. J., Robinaugh D. J., Perugini M., Dalege J., Costantini G., Isvoranu A.-M., Wysocki A. C., van Borkulo C. D., van Bork R., Waldorp L. J. 2021) **Network analysis of multivariate data in psychological science** *Nature Reviews Methods Primers* Nature Publishing Group **1**:1–18

Bos F. M., Snippe E., de Vos S., Hartmann J. A., Simons C. J. P., van der Krieke L., de Jonge P., Wichers M. 2017) **Can We Jump from Cross-Sectional to Dynamic Interpretations of Networks Implications for the Network Perspective in Psychiatry** *Psychotherapy and Psychosomatics* **86**:175–177

Bringmann L. F., Pe M. L., Vissers N., Ceulemans E., Borsboom D., Vanpaemel W., Tuerlinckx F., Kuppens P. 2016) **Assessing Temporal Emotion Dynamics Using Networks** *Assessment*

Bringmann L. F., Vissers N., Wichers M., Geschwind N., Kuppens P., Peeters F., Borsboom D., Tuerlinckx F. 2013) **A network approach to psychopathology: new insights into clinical longitudinal data** *PLoS One* **8**:e60188

Brose A., Schmiedek F., Koval P., Kuppens P. 2015) **Emotional inertia contributes to depressive symptoms beyond perseverative thinking** *Cognition & Emotion* **29**:527–538

Brown V. M., Zhu L., Solway A., Wang J. M., McCurry K. L., King-Casas B., Chiu P. H. 2021) **Reinforcement Learning Disruptions in Individuals With Depression and Sensitivity to Symptom Change Following Cognitive Behavioral Therapy** *JAMA Psychiatry* **78**:1113–1122

Brunton S. L., Kutz J. N. 2019) **Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control** Cambridge: Cambridge University Press

Carey T. A., Griffiths R., Dixon J. E., Hines S. 2020) **Identifying Functional Mechanisms in Psychotherapy: A Scoping Systematic Review** *Frontiers in Psychiatry* **11**:291

Cowen A. S., Keltner D. 2017) **Self-report captures 27 distinct categories of emotion bridged by continuous gradients** *Proceedings of the National Academy of Sciences of the United States of America* National Academy of Sciences **114**:E7900-E7909

Daly M., Baumeister R. F., Delaney L., MacLachlan M. 2014) **Self-control and its relation to emotions and psychobiology: evidence from a Day Reconstruction Method study** *Journal of Behavioral Medicine* **37**:81–93

Dercon Q., Mehrhof S. Z., Sandhu T. R., Hitchcock C., Lawson R. P., Pizzagalli D. A., Dalgleish T., Nord C. L. 2023) **A core component of psychological therapy causes adaptive changes in computational learning mechanisms** *Psychological Medicine* Cambridge University Press :1–11

Domes G., Schulze L., Bottger M., Grossmann A., Hauenstein K., Wirtz P. H., Heinrichs M., Herpertz S. C. 2010) **The neural correlates of sex differences in emotional reactivity and emotion regulation** *Human Brain Mapping* **31**:758–769 https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.20903

Dorfel D., Lamke J.-P., Hummel F., Wagner U., Erk S., Walter H. 2014) **Common and differential neural networks of emotion regulation by Detachment, Reinterpretation, Distraction, and Expressive Suppression: a comparative fMRI investigation** *Neuroimage* **101**:298309

Durbin J., Koopman S. 2012) **Time Series Analysis by State Space Methods: Second Edition** OUP Oxford

Durstewitz D., Huys Q. J. M., Koppe G. 2020) **Psychiatric Illnesses as Disorders of Network Dynamics** *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging* Elsevier BV

Eippert F., Veit R., Weiskopf N., Erb M., Birbaumer N., Anders S. 2007) **Regulation of emotional responses elicited by threat-related stimuli** *Human Brain Mapping* **28**:409–423 https://onlinelibrary.wiley.com/doi/pdf/10.1002/hbm.20291

Eldar E., Rutledge R. B., Dolan R. J., Niv Y. 2016) **Mood as Representation of Momentum** *Trends in Cognitive Sciences* Elsevier BV **20**:15–24

Epskamp S., Borsboom D., Fried E. I. 2018) **Estimating psychological networks and their accuracy: A tutorial paper** *Behavior research methods* **50**:195–212

Faul F., Erdfelder E., Buchner A., Lang A.-G. 2009) **Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses** *Behavior Research Methods* **41**:1149–1160

Faul F., Erdfelder E., Lang A.-G., Buchner A. 2007) **G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences** *Behavior Research Methods* **39**:175–191

Goldfried M. R. 2013) **What should we expect from psychotherapy?** *Clinical Psychology Review* Netherlands: Elsevier Science **33**:862–869

Grahek I., Everaert J., Krebs R. M., Koster E. H. W. 2018) **Cognitive Control in Depression: Toward Clinical Models Informed by Cognitive Neuroscience** *Clinical Psychological Science* SAGE Publications Inc **6**:464–480

Gross J. J. 1998) **Antecedent- and response-focused emotion regulation: divergent consequences for experience, expression, and physiology** *J Pers Soc Psychol* **74**:224–237

Gross J. J. 2015) **Emotion Regulation: Current Status and Future Prospects** *Psychological Inquiry* Routledge **26**:1–26 https://doi.org/10.1080/1047840X.2014.940781

Hayes S. C., Luoma J. B., Bond F. W., Masuda A., Lillis J. 2006) **Acceptance and Commitment Therapy: Model, processes and outcomes** *Behaviour Research and Therapy* Elsevier BV **44**:1–25

Hitchcock P. F., Fried E. I., Frank M. J. 2022) **Computational Psychiatry Needs Time and Context** *Annual review of psychology* **73**:243–270

Holmes E. A., Ghaderi A., Harmer C. J., Ramchandani P. G., Cuijpers P., Morrison A. P., Roiser J. P., Bockting C. L. H., O'Connor R. C., Shafran R., Moulds M. L., Craske M. G. 2018) **The Lancet Psychiatry Commission on psychological treatments research in tomorrow's science** *The Lancet Psychiatry* **5**:237–286

Hosenfeld B., Bos E. H., Wardenaar K. J., Conradi H. J., Maas H. L. J. v. d., Visser I., Jonge P. D. 2015) **Major depressive disorder as a nonlinear dynamic system: Bimodality in the frequency distribution of depressive symptoms over time** *BMC Psychiatry* BioMed Central Ltd **15**

Houben M., Noortgate W. V. D., Kuppens P. 2015) **The relation between short-term emotion dynamics and psychological well-being: A meta-analysis** *Psychological Bulletin* American Psychological Association Inc **141**:901–930

Huys Q. J. M., Russek E. M., Abitante G., Kahnt T., Gollan J. K. 2022) **Components of Behavioral Activation Therapy for Depression Engage Specific Reinforcement Learning Mechanisms in a Pilot Study** *Computational Psychiatry* Ubiquity Press **6**:238–255

Joormann J., Tanovic E. 2015) **Cognitive vulnerability to depression: examining cognitive control and emotion regulation** *Current Opinion in Psychology* **4**:86–92

Kazdin A. E. 2007) **Mediators and mechanisms of change in psychotherapy research** *Annual Review of Clinical Psychology* **3**:1–27

Kazdin A. E. 2009) **Understanding how and why psychotherapy leads to change** *Psychotherapy Research: Journal of the Society for Psychotherapy Research* **19**:418–428

Kendler K. S. 2016) **The nature of psychiatric disorders** *World psychiatry : official journal of the World Psychiatric Association (WPA)* John Wiley and Sons Inc **15**:5–12

Klug G., Henrich G., Filipiak B., Huber D. 2012) **Trajectories and Mediators of Change in Psychoanalytic, Psychodynamic, and Cognitive Behavioral Therapy** *Journal of the American Psychoanalytic Association* **60**:598–605

Koenigsberg H. W., Fan J., Ochsner K., Liu X., Guise K. G., Pizzarello S., Dorantes C., Guerreri S., Tecuta L., Goodman M., New A., Siever L. J. 2009) **Neural Correlates of the Use of Psychological Distancing to Regulate Responses to Negative Social Cues: A Study of Patients with Borderline Personality Disorder** *Biological psychiatry* **66**:854

Koval P., Kuppens P., Allen N. B., Sheeber L. 2012) **Getting stuck in depression: the roles of rumination and emotional inertia** *Cognition & emotion* **26**:1412–1427

Koval P., Pe M. L., Meers K., Kuppens P. 2013) **Affect dynamics in relation to depressive symptoms: variable, unstable or inert?** *Emotion (Washington, D.C.)* **13**:1132–1141

Kroenke K., Spitzer R. L., Williams J. B. 2001) **The PHQ-9: validity of a brief depression severity measure** *Journal of general internal medicine* **16**:606–613

Kuppens P., Allen N. B., Sheeber L. B. 2010) **Emotional inertia and psychological maladjustment** *Psychol Sci* **21**:984–991

Kuppens P., Sheeber L. B., Yap M. B. H., Whittle S., Simmons J. G., Allen N. B. 2012) **Emotional inertia prospectively predicts the onset of depressive disorder in adolescence** *Emotion* **12**:283–289

Kuppens P., Verduyn P. 2017) **Emotion dynamics** *Current Opinion in Psychology* **17**:2226

Lange J., Heerdink M. W., van Kleef G. A. 2022) **Reading emotions, reading people: Emotion perception and inferences drawn from perceived emotions** *Current Opinion in Psychology* **43**:85–90

Lapate R. C., Heller A. S. 2020) **Context matters for affective chronometry** *Nature Human Behaviour* Nature Publishing Group **4**:688–689

Leemput I. A. v. d., Wichers M., Cramer A. O. J., Borsboom D., Tuerlinckx F., Kuppens P., Nes E. H. v., Viechtbauer W., Giltay E. J., Aggen S. H., Derom C., Jacobs N., Kendler K. S., Maas H. L. J. v. d., Neale M. C., Peeters F., Thiery E., Zachar P., Scheffer M. 2014) **Critical slowing down as early warning for the onset and termination of depression** *Proc Natl Acad Sci USA* **111**:87–92

Luborsky L., Rosenthal R., Diguer L., Andrusyna T. P., Berman J. S., Levitt J. T., Seligman D. A., Krause E. D. 2002) **The dodo bird verdict is alive and well—mostly** *Clin Psychol Sci Pract*

Malamud J., Huys Q. J. M. 2024) **Characterizing the dynamics, reactivity and controllability of moods in depression with a Kalman filter** *PLoS Comput Biol*

McRae K., Gross J. J. 2020) **Emotion regulation** *Emotion* US: American Psychological Association **20**:1

McRae K., Jacobs S. E., Ray R. D., John O. P., Gross J. J. 2012) **Individual differences in reappraisal ability: Links to reappraisal frequency, well-being, and cognitive control** *Journal of Research in Personality* **46**:2–7

Mitchell J. 2021) **Affective shifts: mood, emotion and well-being** *Synthese* **199**:11793–11820

Nelson B., McGorry P. D., Wichers M., Wigman J. T. W., Hartmann J. A. 2017) **Moving From Static to Dynamic Models of the Onset of Mental Disorder: A Review** *JAMA psychiatry* **74**:528–534

Norbury A., Hauser T. U., Fleming S., Dolan R. J., Huys Q. 2023) **Different components of cognitive-behavioural therapy affect specific cognitive mechanisms** *Sci Adv*

Oaten M., Cheng K. 2006) **Improved Self-Control: The Benefits of a Regular Program of Academic Study** *Basic and Applied Social Psychology* Routledge **28**:1–16 https://doi.org/10.1207

/s15324834basp2801_1

Ochsner K. N., Ray R. D., Cooper J. C., Robertson E. R., Chopra S., Gabrieli J. D. E., Gross J. J. 2004) **For better or for worse: neural systems supporting the cognitive down- and up-regulation of negative emotion** *Neuroimage* **23**:483–499

Palan S., Schitter C. 2018) **Prolific.ac—A subject pool for online experiments** *Journal of Behavioral and Experimental Finance* Elsevier **17**:22–27

Paschke L. M., Dorfel D., Steimke R., Trempler I., Magrabi A., Ludwig V. U., Schubert T., Stelzel C., Walter H. 2016) **Individual differences in self-reported self-control predict successful emotion regulation** *Social Cognitive and Affective Neuroscience* **11**:1193–1204

Pe M. L., Brose A., Gotlib I. H., Kuppens P. 2016) **Affective updating ability and stressful events interact to prospectively predict increases in depressive symptoms over time** *Emotion* **16**:73–82

Pe M. L., Kircanski K., Thompson R. J., Bringmann L. F., Tuerlinckx F., Mestdagh M., Mata J., Jaeggi S. M., Buschkuehl M., Jonides J., Kuppens P., Gotlib I. H. 2015) **EmotionNetwork Density in Major Depressive Disorder** *Clinical Psychological Science* **3**:292–300 https://doi.org/10.1177/2167702614540645

Peer E., Brandimarte L., Samat S., Acquisti A. 2017) **Beyond the Turk: Alternative platforms for crowdsourcing behavioral research** *Journal of Experimental Social Psychology* Netherlands: Elsevier Science **70**:153–163

Powers J. P., LaBar K. S. 2019) **Regulating emotion through distancing: A taxonomy, neurocognitive model, and supporting meta-analysis** *Neuroscience & Biobehavioral Reviews* Elsevier BV **96**:155–173

Reiter A. M. F., Atiya N. A. A., Berwian I. M., Huys Q. J. M. 2021) **Neuro-cognitive processes as mediators of psychological treatment effects** *Current Opinion in Behavioral Sciences* Elsevier BV **38**:103–109

Roweis S., Ghahramani Z. 1999) **A unifying review of linear gaussian models** *Neural computation* **11**:305–345

Rutledge R. B., Skandali N., Dayan P., Dolan R. J. 2014) **A computational and neural model of momentary subjective well-being** *Proceedings of the National Academy of Sciences* **111**:12252

Schwarz G. 1978) **Estimating the Dimension of a Model** *The Annals of Statistics* Institute of Mathematical Statistics **6**:461–464

Snyder H. R. 2013) **Major depressive disorder is associated with broad impairments on neuropsychological measures of executive function: A meta-analysis and review** *Psychological Bulletin* US: American Psychological Association **139**:81–132

Somerville M., MacIntyre H., Harrison A., Mauss I. 2022) **Emotion controllability beliefs and young people's anxiety and depression symptoms: A systematic review** *Adolesc Res Rev*

Sperry S. H., Walsh M. A., Kwapil T. R. 2020) **Emotion dynamics concurrently and prospectively predict mood psychopathology** *Journal of Affective Disorders* Elsevier B.V **261**:67–75

Spitzer R. L., Kroenke K., Williams J. B. W., Löwe B. 2006) **A brief measure for assessing generalized anxiety disorder: the GAD-7** *Archives of internal medicine* **166**:1092–1097

Staudinger M. R., Erk S., Abler B., Walter H. 2009) **Cognitive reappraisal modulates expected value and prediction error encoding in the ventral striatum** *NeuroImage* **47**:713–721

Tangney J. P., Baumeister R. F., Boone A. L. 2004) **High self-control predicts good adjustment, less pathology, better grades, and interpersonal success** *Journal of Personality* **72**:271–324

Trull T. J., Lane S. P., Koval P., Ebner-Priemer U. W. 2015) **Affective dynamics in psychopathology** *Emotion Review* SAGE Publications **7**:355–361

Vanhasbroeck N., Loossens T., Anarat N., Ariens S., Vanpaemel W., Moors A., Tuerlinckx F. 2022) **Stimulus-Driven Affective Change: Evaluating Computational Models of Affect Dynamics in Conjunction with Input** *Affective Science* **3**:559–576

Victor S. E., Klonsky E. D. 2016) **Validation of a brief version of the Difficulties in Emotion Regulation Scale (DERS-18) in five samples** *Journal of Psychopathology and Behavioral Assessment* Germany: Springer **38**:582–589

Villano W. J., Otto A. R., Ezie C. E. C., Gillis R., Heller A. S. 2020) **Temporal dynamics of real-world emotion are more strongly linked to prediction error than outcome** *Journal of Experimental Psychology: General* US: American Psychological Association **149**:1755–1766

Vrticka P., Bondolfi G., Sander D., Vuilleumier P. 2012) **The neural substrates of social emotion perception and regulation are modulated by adult attachment style** *Social Neuroscience* **7**:473–493

Walter H., Kalckreuth A. v., Schardt D., Stephan A., Goschke T., Erk S. 2009) **The temporal dynamics of voluntary emotion regulation** *PLoS One* **4**:e6726

Webb T. L., Miles E., Sheeran P. 2012) **Dealing with feeling: a meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation** *Psychological Bulletin* **138**:775–808

Wichers M., Groot P. C., Psychosystems, Group E. S. M., Group E. W. S. 2016) **Critical Slowing Down as a Personalized Early Warning Signal for Depression** *Psychother Psychosom* **85**:114–116

Winecoff A., Clithero J. A., Carter R. M., Bergman S. R., Wang L., Huettel S. A. 2013) **Ventromedial prefrontal cortex encodes emotional value** *J Neurosci* **33**:11032–11039

Winecoff A., LaBar K. S., Madden D. J., Cabeza R., Huettel S. A. 2011) **Cognitive and neural contributors to emotion regulation in aging** *Social Cognitive and Affective Neuroscience* **6**:165–176

Wolpert M., Pote I., Sebastian C. L. 2021) **Identifying and integrating active ingredients for mental health** *The Lancet Psychiatry* **8**:741–743

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Reviewer #1 (Public review):

Summary:

Using sequences of short videos to elicit emotional changes in participants, Malamud & Huys demonstrate how a brief, controlled emotion regulation intervention (distancing) can effectively alter subsequent emotion ratings. The authors employ latent state-space models to capture the trajectories of emotion ratings, leveraging tools from control theory to quantify the intervention's impact on emotion dynamics.

Strengths:

The experiment is well-designed and tailored to the computational modeling approach advanced in the paper. It also relies on a selection of stimuli that were previously validated. Within the constraints of a controlled experiment, the intervention successfully implements a relatively common tool of psychotherapeutic treatment, ensuring its clinical relevance.

The computational modeling is grounded in the well-established framework of dynamical systems and control theory. This foundation offers a conceptually clear formalization along with powerful quantification tools that go beyond previous more data-driven approaches.

Overall, the study presents a coherent approach that bridges concepts from clinical psychology and computational theories, providing a timely stepping stone toward advancing quantified, evidence-based psychological interventions targetting emotion control.

Weaknesses:

A primary limitation of this study, acknowledged by the authors, is its reliance on self-reports of participants' emotional states. Although considerable effort was made to minimize expectation effects, further research is needed to confirm that the observed behavioral changes reflect genuine alterations in emotional states. Additionally, the generalizability of the findings to long-term remediation strategies remains an open question.

Second, the statistical analysis, particularly the computational approach, sometimes lacks sufficient detail and refinement. While I will not elaborate on specific points here, one notable issue is the interpretation of the intrinsic matrix (A). The model-free analysis reveals correlations between emotions at a given time or within an emotional state across time points. However, it does not provide evidence to support lagged interactions across states that would justify non-diagonal elements in A. The other result concerning the dynamics matrix only highlights a trend in the dominant eigenvalue, which is difficult to interpret in isolation. The absence of a statistically significant group x intervention interaction furthermore makes this finding a little compelling. This weakens the study's conclusions about the importance of intrinsic dynamics, as claimed in the title.

Finally, to avoid potential misunderstandings of their work, the authors should be more careful about their use of terms pertaining to the control theory and take the time to properly define them. For example, the "controllability" of emotional states can either denote that those states are more changeable (control theory definition), or, conversely, more tightly regulated (common interpretation, as used in the abstract). This is true for numerous terms (stability, sensitivity, Gramian, etc.) for which no clear definition nor references are provided. Readers unfamiliar with the framework of control theory will likely be at a loss without more guidance.

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Reviewer #2 (Public review):

Summary:

In this well-conceived and timely study, the authors assess the controllability of emotions in a quantitative way using the framework of control theory. They use a controlled distancing intervention halfway through an emotion rating task where emotion-inducing short videos from a validated database are shown and find that the intervention enables a better controllability of externally induced emotions in the experimental group.

Strengths:

It is a highly original idea to address the external controllability of emotions using the formal framework of control theory. It is also a very propitious approach to take what could be called a 'micro-therapeutic' perspective which looks at the immediate effect of an intervention instead of the 'macro-therapeutic' mid- or long-term effect of a whole course of therapy.

Weaknesses:

Acquiring data online inevitably gives rise to selection and self-selection effects. This needs to be acknowledged clearly. Exacerbating this, participant remuneration seems low at an amount below the minimum or living wage in Western countries (do the authors know where their participants came from?).

Another concern is that the intervention does not simply take place before the second block begins but is ongoing during the whole of the second block in that it is integrated into the phrasing of the task on each trial. It is therefore somewhat misleading to speak of a period 'after the intervention', and it would have been interesting to assess the effect of this by including a third group where the phrasing does not change, but the floating leaves intervention takes place.

As mentioned in the Limitations section, observation noise was assumed and not estimated. While this is understandable in this case, the effect of this assumption could have been assessed by simulation with varying levels of observation (and process) noise.

Relatedly, the reliance on formal model comparison is unfortunate since the outcome of such comparisons is easily influenced by slight changes to assumptions such as noise levels. An alternative approach would have been to develop a favoured model based on its suitability to address the research question and its ability, established by simulation, to distill relevant changes of behaviour into reliable parameter estimates.

The statistical analyses clearly show the limitations of classical statistical testing with highly complex models of the kind the authors (commendably) use. Hunting for statistically significant interactions in a multivariate repeated-measures design relying on inputs from time series-derived point estimates is a difficult proposition. While the authors make the best of the bad situation they create by using null-hypothesis significance testing, a more promising approach would have been to estimate parameters using a sampler like Stan or PyMC and then draw conclusions based on posterior predictive simulations.

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Reviewer #3 (Public review):

Summary:

The manuscript takes a dynamical systems perspective on emotion regulation, meaning that rather than a simplistic model conceptualising regulation as applying to a single emotion (e.g. regulation of sadness), emotion regulation could cause a shift in the dynamics of a whole system of emotions (which are linked mathematically to one another). This builds on the idea that there are 'attractor states' of emotions between which people transition, governed by both the system's intrinsic characteristics (e.g. temporal autocorrelation of a particular emotion/person) and external driving forces (having a stressful week). Conceptually this is a very useful advance because it is very unlikely that emotions are elicited (or reduced) singly, without affecting other emotions. This paper is a timely implementation of these ideas in the context of psychotherapeutic intervention, distancing, which participants were trained (randomised) to perform while watching emotion-inducing videos.

The authors' main conclusion is that distancing both stabilises specific emotional patterns and reduces the impact of external video clips. I would consider these results strong and believable, and to have the potential to impact models of emotion regulation as well as the field's broader views on the mechanisms of psychological therapies.

Strengths:

This paper has very many strengths: I would especially note the authors' very-well-matched active control condition and the robustness of their model comparison approach. One feature of the authors' approach is that they explicitly add noise - not what you typically see in an emotion time-series analysis - which allows participants to make errors in their own subjective ratings (a reasonable thing to assume); this noise can then be smoothed during filtering. In their model comparison approach, they explicitly test whether a true dynamical system explains emotion change/emotion regulation effect on emotions - demonstrating that both intrinsic dynamics and external inputs were needed to explain subjective emotion. Powerfully, they also used this approach to test the differential effects of the treatment groups (see below).

The main result seems quite robust statistically. Verifying the effects of the distancing intervention on emotion, the authors found an interaction between time (pre- to post-intervention) and intervention group (distancing vs. relaxation) suggesting that distancing (but not relaxation) reduced ratings of almost all emotions. Participants allocated to the distancing intervention also showed decreased variability of emotion ratings compared to those in the relaxation intervention (though note this interaction was not significant).

Using a model comparison approach, the authors then demonstrated that whilst the control group was best explained by a model that did not change its dynamics of emotions, the active intervention (distancing) group was best explained by a model that captured both changing emotion dynamics and a changing input weights (influence of the videos) - results confirmed in follow-up analyses. This is convincing evidence that emotion regulation strategies may specifically affect the dynamics of emotions - both their relationships to one another and their susceptibility to changes evoked by external influences.

The authors also perform analyses that suggest their result is not attributable to a demand effect (finding that participants were quicker during the control intervention, which one would expect if they had already decided how to respond in advance of the emotion question). I personally also think a demand effect is unlikely given the robustness of their control intervention (which participants would be just as likely to interpret as mental health-enhancing training as distancing), and I am convinced by the notion that demand effects would be unlikely to elicit their more specific effects on the dynamic quality of emotions.

Weaknesses:

An interesting but perhaps at present slightly confusing aspect of their described results relates to the 'controllability' of emotions, which they define as their susceptibility to external inputs. Readers should note this definition is (as I understand it) quite distinct from, and sometimes even orthogonal to, concepts of emotional control in the emotion literature, which refer to intentional control of emotions (by emotion regulation strategies such as distancing). The authors also use this second meaning in the discussion. Because of the centrality of control/controllability (in both meanings) to this paper, at present it is key for readers to bear these dual meanings in mind for juxtaposed results that distancing "reduces controllability" while causing "enhanced emotional control".

As above the authors use an active control - a relaxation intervention - which is extremely closely matched with their active intervention (and a major strength). However, there was an additional difference between the groups (as I currently understand it): "in the group allocated to the distancing intervention, the phrasing of the question about their feelings in the second video block reminded participants about the intervention, stating: "You observed your emotions and let them pass like the leaves floating by on the stream." I do wonder if the effects of distancing also have been partially driven by some degree of reappraisal (considered a separate emotion regulation strategy) since this reminder might have evoked retrospective changes in ratings.

Not necessarily a weakness, but an unanswered question is exactly how distancing is producing these effects. As the authors point out, there is a possibility that eye-movement avoidance of the more emotionally salient aspects of scenes could be changing participants' exposure to the emotions somewhat. Not discussed by the authors, but possibly relevant, is the literature on differences between emotion types on oculomotor avoidance, which could have contributed to differential effects on different emotions.

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Author response:

> ***Reviewer 1:***
>
> *A primary limitation of this study, acknowledged by the authors, is its reliance on self-reports of participants' emotional states. Although considerable effort was made to minimize expectation effects, further research is needed to confirm that the observed behavioral changes reflect genuine alterations in emotional states.*

Thank you very much for raising this point. We fully agree that self-reported emotional states are inherently subjective and that the ramifications of this need to be clarified in the manuscript. However, we would suggest that the focus on self-report may be a strength rather than a limitation. First, the regularities and rules underlying and determining emotional self-report are of primary importance and interest in their own right, and the work presented here does, we believe, shed light on a rich structure present in multivariate timeseries of subjective self-reports and their response to external inputs. Second, there is no clear definition of what a ”genuine emotion state” might be; particularly if there is a discrepancy with self-reported emotions.

> *Additionally, the generalizability of the findings to long-term remediation strategies remains an open question.*

Yes, we agree that what we have described is limited to a short-term intervention and change.

Whether these changes bear on longer-term changes remains to be assessed. Furthermore, the mechanisms or processes that would support such a maintenance are of substantial interest, and will be the focus of future work.

> *Second, the statistical analysis, particularly the computational approach, sometimes lacks sufficient detail and refinement. While I will not elaborate on specific points here, one notable issue is the interpretation of the intrinsic matrix (A). The model-free analysis reveals correlations between emotions at a given time or within an emotional state across time points. However, it does not provide evidence to support lagged interactions across states that would justify non-diagonal elements in A. The other result concerning the dynamics matrix only highlights a trend in the dominant eigenvalue, which is difficult to interpret in isolation. The absence of a statistically significant group x intervention interaction furthermore makes this finding a little compelling. This weakens the study's conclusions about the importance of intrinsic dynamics, as claimed in the title.*

We appreciate the reviewer's detailed feedback on the statistical analysis and interpretation of the intrinsic dynamics matrix. It is true that the model-free analysis as presented focuses on within-state correlations and that we have not provided such model-free evidence for lagged interactions across states. We do note that the model comparison suggested that the intervention caused changes in the full A matrix. This would be unlikely if there had not been meaningful cross-emotion lagged effects. Similarly, inference of the A matrix could have revealed a diagonal matrix, and we preferred not to impose such an assumption a priori, as it is very restrictive. Nevertheless, in the absence of a statistically significant group x intervention interaction, the findings regarding the A matrix are less compelling than those related to the control analyses. While this is likely due to a lack of statistical power, these are important points which we will consider in more detail in the revision.

> *Finally, to avoid potential misunderstandings of their work, the authors should be more careful about their use of terms pertaining to the control theory and take the time to properly define them. For example, the ”controllability” of emotional states can either*

> *denote that those states are more changeable (control theory definition), or, conversely, more tightly regulated (common interpretation, as used in the abstract). This is true for numerous terms (stability, sensitivity, Gramian, etc.) for which no clear definition nor references are provided. Readers unfamiliar with the framework of control theory will likely be at a loss without more guidance.*

Thank you for this point. We recognize the potential for misunderstanding due to the dual usage of terms such as ”controllability” and will improve the clarity to avoid any misunderstanding.

> ***Reviewer 2:***
>
> *Acquiring data online inevitably gives rise to selection and self-selection effects. This needs to be acknowledged clearly. Exacerbating this, participant remuneration seems low at an amount below the minimum or living wage in Western countries (do the authors know where their participants came from?).*

Thank you for this point. We certainly agree that different experimental settings can induce different biases, and this is no different for online settings. However, online tasks such as the one used here, have become accepted, and there is now a substantial literature showing that in-lab effects are often well-replicated in online settings (Gillan and Rutledge, 2021) . For the current study, it is not clear that an inperson setting may not induce comparably complex biases, e.g. to do with differences between experimenters. All participants were from the UK. Remuneration rates were comparable to other experimental settings, in keeping with other online studies, UK living wage recommendations, and ultimately determined according to institutional ethical guidance.

> *Another concern is that the intervention does not simply take place before the second block begins but is ongoing during the whole of the second block in that it is integrated into the phrasing of the task on each trial. It is therefore somewhat misleading to speak of a period 'after the intervention', and it would have been interesting to assess the effect of this by including a third group where the phrasing does not change, but the floating leaves intervention takes place.*

Thank you for this point. We acknowledge that the phrasing of the emotion question in the second block may have influenced the observed effects. Including a third group without the reminder would have provided valuable insights and is an important consideration for future studies. We will acknowledge this limitation.

> *As mentioned in the Limitations section, observation noise was assumed and not estimated. While this is understandable in this case, the effect of this assumption could have been assessed by simulation with varying levels of observation (and process) noise.*

Thank you for this comment. We would like to clarify that both observation noise and process noise were estimated in the analyses. We will ensure this is emphasized better in the revised version to avoid future misunderstandings.

> *Relatedly, the reliance on formal model comparison is unfortunate since the outcome of such comparisons is easily influenced by slight changes to assumptions such as noise levels. An alternative approach would have been to develop a favoured model based on its suitability to address the research question and its ability, established by simulation, to distill relevant changes of behaviour into reliable parameter estimates.*

We agree that model comparison alone is insufficient. This is why we have also included extensive simulations, including posterior predictive checks, and have followed established best-practice procedures (Wilson and Collins, 2019). We have focused on a relatively simple model space to avoid overfitting to the dataset, and hence reduce the risk of spurious findings. While we agree that outcomes will be influenced by underlying assumptions, this would persist with the suggested approach of relying on a favoured model. Simulations themselves rely on predefined structures and noise specifications, which inherently shape parameter recovery and inference. Relying only on a favoured model might risk model misspecification, whereby the model may not actually capture the data, and the parameters intended to capture the intervention effect could be confounded. We will clarify the reasoning behind our approach in the revised version.

> *The statistical analyses clearly show the limitations of classical statistical testing with highly complex models of the kind the authors (commendably) use. Hunting for statistically significant interactions in a multivariate repeated-measures design relying on inputs from time seriesderived point estimates is a difficult proposition. While the authors make the best of the bad situation they create by using null-hypothesis significance testing, a more promising approach would have been to estimate parameters using a sampler like Stan or PyMC and then draw conclusions based on posterior predictive simulations.*

This comment raises several interesting points. First, we agree that the value of classical test on individual parameters within such complex situations is limited. This is why our main focus is on global measures like model comparison. Our use of the classical tests is more to support the understanding of the nature of the data, i.e. they have a more descriptive aim. We will hope to clarify this further in the revision. Second, in terms of sampling, we would like to emphasize that the Kalman filter is both efficient and analytical tractable, making it well-suited to our data and research question. It may have been possible to use sampling to obtain posterior distributions rather than point estimates. However, we did not judge this to be worth the (substantial) additional computational cost.

> ***Reviewer 3:***
>
> *An interesting but perhaps at present slightly confusing aspect of their described results relates to the 'controllability' of emotions, which they define as their susceptibility to external inputs. Readers should note this definition is (as I understand it) quite distinct from, and sometimes even orthogonal to, concepts of emotional control in the emotion literature, which refer to intentional control of emotions (by emotion regulation strategies such as distancing). The authors also use this second meaning in the discussion. Because of the centrality of control/controllability (in both meanings) to this paper, at present it is key for readers to bear these dual meanings in mind for juxtaposed results that distancing "reduces controllability" while causing "enhanced emotional control".*

We fully agree with the reviewer's observation that "controllability" can be interpreted in different ways. we will revise the text to ensure consistent usage and explicitly state the distinction between the control theory definition of controllability and its interpretation in the emotion regulation literature.

> *As above the authors use an active control - a relaxation intervention - which is extremely closely matched with their active intervention (and a major strength). However, there was an additional difference between the groups (as I currently understand it): "in the group allocated to the distancing intervention, the phrasing of the question about their feelings in the second video block reminded participants about the intervention, stating: "You*

> *observed your emotions and let them pass like the leaves floating by on the stream." I do wonder if the effects of distancing also have been partially driven by some degree of reappraisal (considered a separate emotion regulation strategy) since this reminder might have evoked retrospective changes in ratings.*

We appreciate this substantial point. While our study was designed to isolate the effects of distancing, we acknowledge that elements of reappraisal may also have influenced the results. We will discuss this in the revised version. Additionally, as noted in our response to Reviewer 2, including a third group without the reminder could have provided valuable information, and we consider this to be an important direction for future research.

> *Not necessarily a weakness, but an unanswered question is exactly how distancing is producing these effects. As the authors point out, there is a possibility that eye-movement avoidance of the more emotionally salient aspects of scenes could be changing participants' exposure to the emotions somewhat. Not discussed by the authors, but possibly relevant, is the literature on differences between emotion types on oculomotor avoidance, which could have contributed to differential effects on different emotions.*

Thank you very much for these suggestions. It is very true that different emotions can elicit different patterns of oculomotor avoidance, which could have contributed to our observed effects. Research suggests that emotions such as disgust are associated with visual avoidance (Armstrong et al., 2014; Dalmaijer et al., 2021), whereas anxiety and other negative emotions exhibited increased attentional bias after fear conditioning (Kelly and Forsyth, 2009; Pischek-Simpson et al., 2009). It would be very interesting to repeat the experiment with eye-tracking to examine these possibilities. What would be particularly interesting to examine is whether a distancing intervention induces multiple, emotionally-specific behaviours, or not.

References

Armstrong, T., McClenahan, L., Kittle, J., and Olatunji, B. O. (2014). Don't look now! Oculomotor avoidance as a conditioned disgust response. Emotion (Washington, D.C.), 14(1):95–104.

Dalmaijer, E. S., Lee, A., Leiter, R., Brown, Z., and Armstrong, T. (2021). Forever yuck: Oculomotor avoidance of disgusting stimuli resists habituation. Journal of Experimental Psychology. General, 150(8):1598– 1611.

Gillan, C. M. and Rutledge, R. B. (2021). Smartphones and the Neuroscience of Mental Health. Annual Review of Neuroscience, 44(Volume 44, 2021):129–151. Publisher: Annual Reviews.

Kelly, M. M. and Forsyth, J. P. (2009). Associations between emotional avoidance, anxiety sensitivity, and reactions to an observational fear challenge procedure. Behaviour Research and Therapy, 47(4):331–338. Place: Netherlands Publisher: Elsevier Science.

Pischek-Simpson, L. K., Boschen, M. J., Neumann, D. L., and Waters, A. M. (2009). The development of an attentional bias for angry faces following Pavlovian fear conditioning. Behaviour Research and Therapy, 47(4):322–330.

Wilson, R. C. and Collins, A. G. (2019). Ten simple rules for the computational modeling of behavioral data. eLife, 8:e49547. Publisher: eLife Sciences Publications, Ltd.

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