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

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

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Abstract

Our mental health is influenced by the emotional states we experience. Emotional states, in turn, depend on external experiences and internal processes that determine the form and persistence of emotional states. Emotion regulation strategies aim to alter emotional states and are an important element of evidence-based, effective psychotherapeutic interventions. However, the mechanisms by which emotion regulation works remain incompletely understood. Here, we combine experimental induction of momentary emotions with formal dynamical system theory to study how emotion regulation strategies influence emotion dynamics. Participants (N=109) repeatedly reported their multidimensional emotional state while watching brief validated emotional video clips. Participants were then randomized to either an emotion regulation (distancing) or control intervention before watching further video clips. Dynamical and controllability features were inferred from participants' emotion ratings using a Kalman Filter, which captures how emotions evolve, interact, and are affected by external inputs. First, we showed that the Kalman filter provided an adequate account of the data. Emotions were maintained across stimuli, interacted and were richly influenced by emotional stimuli. Second, distancing had a dual effect: It reduced the (external) controllability of emotional states both by stabilizing specific emotional dynamics and by reducing the driving force external emotional stimuli exerted. These results provide a novel, quantitative approach to characterizing how emotions are controlled and how a distancing intervention alters emotional experience. The quantitative characterization of specific psychotherapeutic interventions may help better understand and target interventions.

1 Introduction

Psychotherapeutic interventions are effective treatments for depression and anxiety, but the mechanisms of action responsible for these effects remain poorly understood[1,2]. In addition, there is considerable variation between individuals regarding treatment response[3]. Better targeting psychotherapeutic interventions according to individual needs or characteristics might improve therapy effectiveness. However, 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[4]. However, psychotherapeutic treatments are complex interventions involving many different components[5], likely affecting different behavioural processes and acting via different mechanisms. As such, changes after complete treatment courses are likely to be broad, reflecting the many components of the intervention. By contrast, little research exists on how different components engage specific mechanisms. Here, we build on recent suggestions[6,7,8] and apply cognitive computational techniques to isolated interventions to better characterize and understand the cognitive computational 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[9]. Some emotion regulation strategies can alleviate symptoms of mood disorders and generally improve well-being[10,11,12,13]. 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[14,15]. 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[12,15]. Distancing has been shown to reduce self-reported emotional experience reliably[16,17,18,19] and is associated with decreased amygdala activity even beyond the period of active regulation[20,21,22]. Distancing techniques are practical because they can be implemented in various situations with relatively low attentional demands and behavioural disruption[12]. Here, we examine 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.

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[23,24,25,26]. 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[27,28,29,30]. This work has identified individual differences in affect dynamics which are linked to mood disorders[31,32,33,34,35,36,37]. For example, increased inertia (temporal autocorrelation or how well an emotion can maintain itself) of negative affect has been identified in people with depression[38,39,40,41,42]. 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[24,37,43,32,44]. 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[45]. Before shifting from a happy to a depressed state or vice versa, emotional dynamics were shown to slow down, i.e. temporal autocorrelation increased. This is a key signature of so-called 'critical slowing down' in dynamical systems theory[37,43,32]. Identifying robust markers that indicate the system's resistance or resilience to state changes may provide opportunities for intervention.

Our aim was to examine the dynamic network effect of emotion regulation. This allows us to situate emotion regulation within the formal field of dynamical control theory and employ control theory tools to characterize the emotion system's control properties as a whole. Briefly, a dynamical system is a series of linked differential equations, 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 is a property of both the input sensitivity and the dynamics of the system itself which describes 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.

The dynamical system of emotions and its controllability can be studied by examining time-series of affective self-reports and information about external inputs. Past work mostly focused on the affective self-reports alone and has often neglected the role of external inputs[11]. 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[46,47,48,49].

Here, we hence investigated how external affectively-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 affective state. This enabled us to formally examine the impact of a distancing intervention on emotion dynamics whilst disentangling effects on internal dynamics from alterations of 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 Ethics

The UCL research ethics committee approved the study procedures (REC No 21029/001). Electronic informed consent was obtained from all participants. The study duration was approximately 45 minutes, and participants were reimbursed £7.50/h.

2.2 Participants

109 participants 18 years or older with current UK residence were recruited online on Prolific Academic (www.prolific.co). 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).

2.3 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. Participants were reimbursed through Prolific Academic after completion of study procedures.

In the experiment (Fig. 1), participants saw a sequence of short emotional video clips (cf. 2.3.2 Emotion-Inducing Stimuli), 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[50]. 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 complete 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. 2.3.1 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.

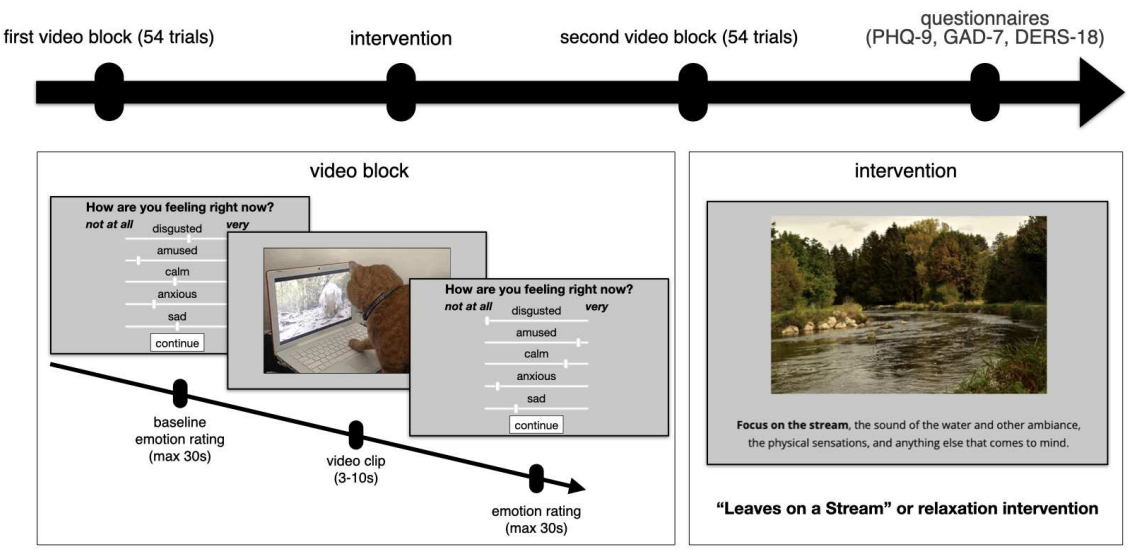

Figure 1: **Task Description**. The large arrow at the top displays the course of the experiment. Both video blocks comprised 54 video clips (2-10 seconds), and after each video clip, participants had 30 seconds to rate their emotional experience based on five emotions. Both blocks also had a baseline 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).

2.3.1 Intervention

The emotion regulation intervention was based on a distancing appraisal strategy, i.e. "Leaves on a Stream" (adapted from Hayes et al.[51]). 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 emotion regulation 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 emotion regulation intervention, the phrasing of the question about their feelings in the second video block reminded participants about the distancing 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.

2.3.2 Emotion-Inducing Stimuli

The video clips stem from a validated database[50] of 2185 videos (link to video database[1]) rated by 853 subjects. The videos were originally collected by searching for specific keywords related to different emotions on search engines and content aggregation websites. They depict various 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 chose video clips with low entropy in ratings and high mean ratings in five target emotion categories: Amusement/Joy, Disgust/Horror, Sadness/Sympathy, Calmness/Aesthetic Adoration and Anxiety/Fear. We identified 20 videos from each of the five categories, resulting in a total of 100 videos. The ratings from Cowen and Keltner[50] for each chosen video and the mean ratings over videos from an emotion category are shown in Supplementary Materials B Video Clips Fig. 7, respectively Fig. 6.

2.3.3 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).

2.3.4 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[52]) and the Generalized Anxiety Disorder Assessment (GAD-7[53]), respectively. In addition, we used a short version of the Difficulties in Emotion Regulation Scale (DERS-18[54]) to assess participants' ability to identify, accept, and manage their emotional experiences. Participants also rated their success in complying with the intervention instructions after the second set of video clips on a Likert scale from "not at all" to "extremely".

2.3.5 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.

[1] https://s3-us-west-1.amazonaws.com/emogifs/uncensored.html

2.4 Computational Modelling

We employed a standard Kalman Filter approach to analyze the observed sequence of emotion state reports $\{\mathbf{x}_t\}_{t=1}^T$ conditional on video inputs $\{\mathbf{u}_t\}_{t=1}^T$ (c.f. 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) emotion 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 $\boldsymbol{\Sigma}$ and $\boldsymbol{\Gamma}$, respectively. This is one of the key differences to standard emotional time-series analyses[55], in that this explicitly allows for noise or errors in the emotion ratings, and this noise can be 'smoothed over' through the filtering process.

2.4.1 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*[2].

We calculated the Bayesian Information Criterion (BIC; Schwarz[56]) 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.

2.4.2 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*)

[2] https://pykalman.github.io/

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).

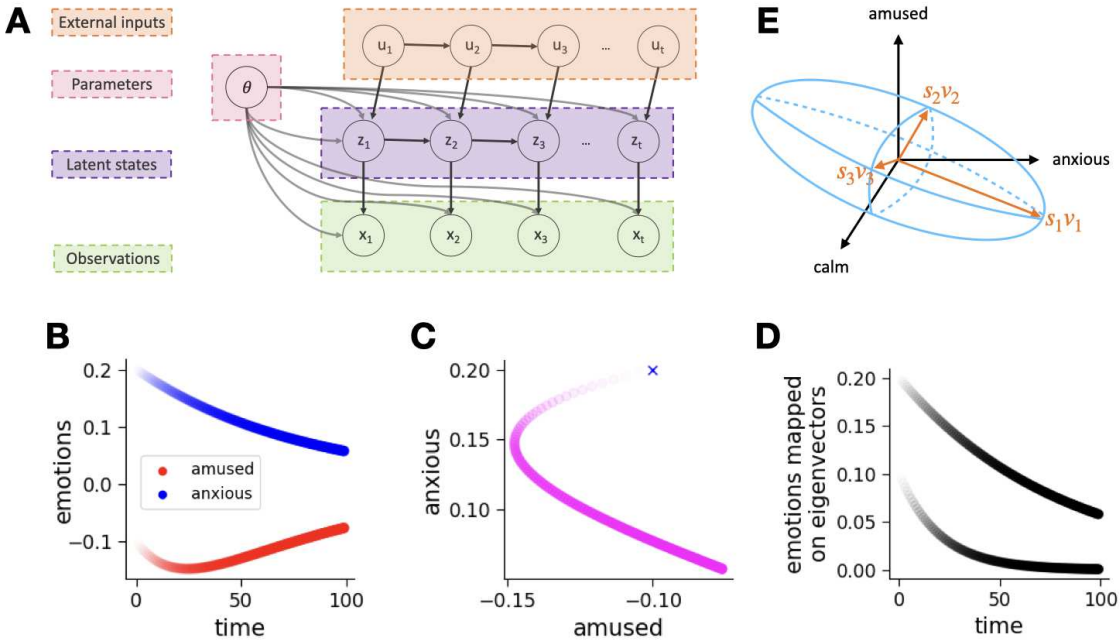

Figure 2: **Dynamical System and Controllability**. **A)** shows a graph visualization of the linear dynamical model, including external inputs ($\mathbf{u}_t$). $\mathbf{z}_t$ describes the latent dynamical states evolving based on a Markov process and directly mapping onto the emotion measurements $\mathbf{x}_t$. **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 $\mathbf{A}$. **E)** The unitary vectors ($\mathbf{V}$) of the controllability matrix define an energy ellipsoid where the unitary directions corresponding to higher singular values ($\mathbf{S}$) 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 ($\mathbf{v}_3$)

2.4.3 Controllability

Next, we investigated the controllability of the dynamical system. Controllability refers to the ability to move a system around in its entire state space using only certain inputs. We computed

the controllability Gramian ($\mathcal{C}$) for each participant as follows:

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

The controllability Gramian ($\mathcal{C}$) 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.

2.5 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

The sequence of emotional videos reliably induced emotions and replicated the ratings from Cowen and Keltner[50] reasonably well (Fig. 3A). Focusing on the first video block before the intervention, each video reliably induced the dominant emotion as intended. Changes in emotion ratings on the dominant emotion for each video were higher than changes in other ratings ($t \in [5.9, 26.2], p < 0.001$; Fig. 3B and Supplementary Material Table 1). Across participants, the correlation between emotion ratings in our sample and that reported by Cowen and Keltner[50] was $r = 0.5$ ($p < 0.001$) for Calmness/Aesthetic Adoration; $r = 0.65$ ($p < 0.001$) for Amusement/Joy; $r = 0.6$ ($p < 0.001$) for Sadness/Sympathy; $r = 0.71$ ($p < 0.001$) for Anxiety/Fear and $r = 0.74$ ($p < 0.001$) for Disgust/Horror.

The videos were complex and induced multi-faceted, high-dimensional emotional states. Changes in non-dominant emotions for each video were significantly different from zero ($|t| \in [5.1, 19.3], p < 0.001$; Fig. 3B and Supplementary Material Table 1) except for the videos from the target category Disgust/Horror ($t = -2.4, p = 0.016$; did not survive multiple comparison correction $p < 0.002$) and Calmness/Aesthetic Adoration ($t = -0.9$, $p = 0.393$), neither of which had a significant effect on ratings of amused. Dynamical components were also apparent in responses. This can be seen in the autocorrelation of each emotion rating, where an effect of the previous time-point is apparent during the rating of the next video ($AR(1) \in [0.07 - 0.25]$, $p \leq 0.001$; cf. Fig. 3C and Supplementary Material Table 2). Dynamic effects can also be observed in the cross-correlation between emotion time-series showing that emotions interact with each other ($|r| \in [0.28 - 0.52]$, $p < 0.001$; cf. Fig. 3D and Supplementary Material Table 3). Finally, the test-retest reliability of emotions elicited by repeated video clips varied accordingly to emotion type (cf. Supplementary Materials Table 4). Specifically, it was observed to be high for Disgust/Horror (video sequence 1: $ICC = 0.8$, $p < 0.001$, video sequence 2: $ICC = 0.55$, $p = 0.02$), but only moderate for Amusement/Joy (video sequence 1: $ICC = 0.34$, $p = 0.033$, video sequence 2: $ICC = 0.34$, $p = 0.031$). This is perhaps unsurprising as Amusement/Joy is partially a function of surprise, which is reduced with repetition. 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.

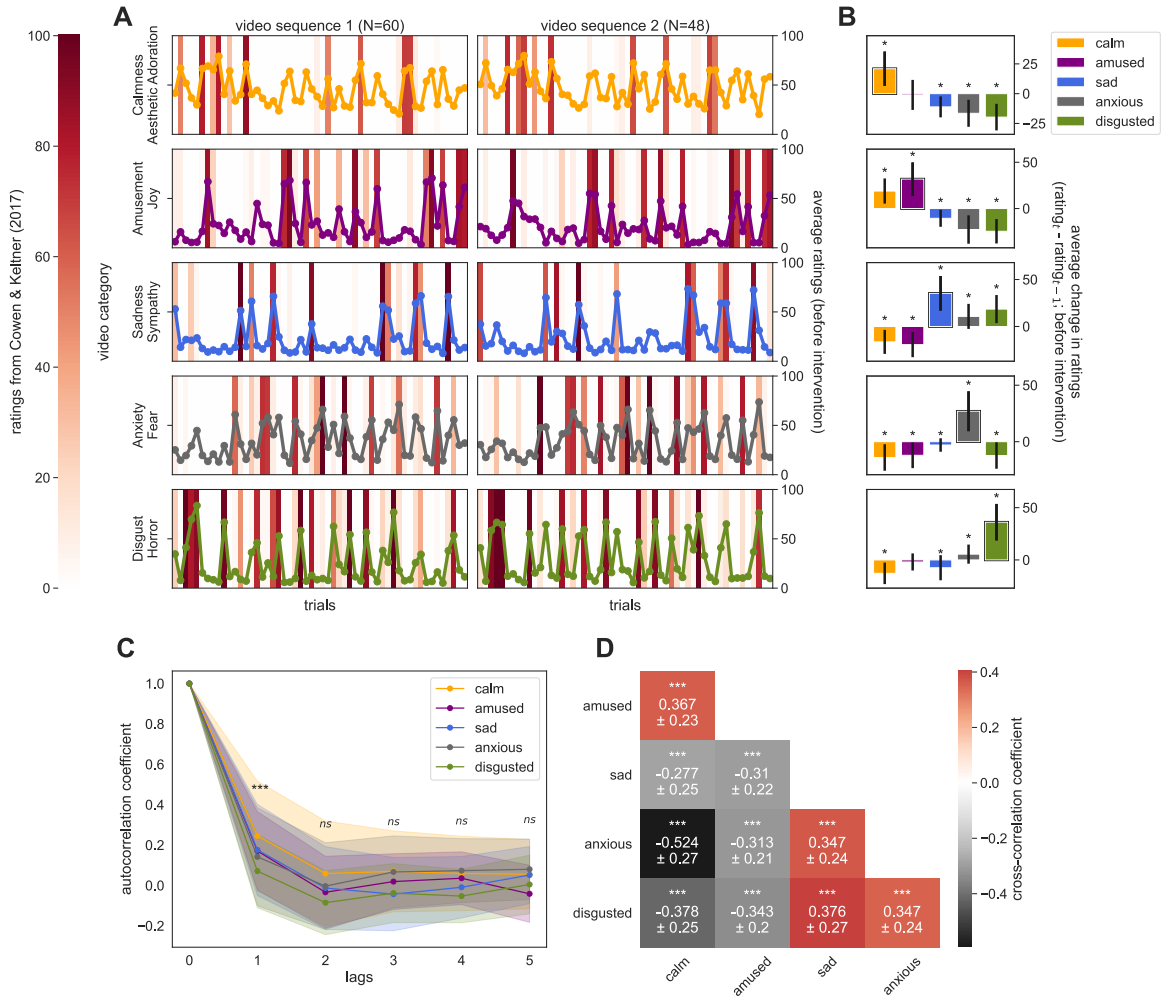

Figure 3: **Emotion Ratings**. **A)** The heatmap shows for each emotion eliciting video category the ratings from Cowen and Keltner[50] averaged over the two emotion categories of interest (left y-axis). The coloured lines with dots report the emotion ratings from our experiment for each emotion after 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

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.

3.4 Effects of Distancing on Emotional Responses

We first examined the effect of the intervention on the average reported emotions (Fig. 5A). The mean ratings averaged over trials in the video blocks after the intervention were significantly different between the emotion regulation and the control group ($T^2 = 4.48$, $F = 4.71$, $p < 0.001$). By contrast, mean ratings were similar before the intervention ($T^2 = 6.53$, $F = 1.26$, $p = 0.29$). The within-subject change in average ratings (after minus before intervention) differed significantly ($T^2 = 52.66$, $F = 10.14$, $p < 0.001$). Additionally we observed a significant interaction between time and intervention group ($F(5, 208) = 2.6$, $p = 0.026$). At the group-level, all emotion ratings were significantly reduced after the emotion regulation 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 5).

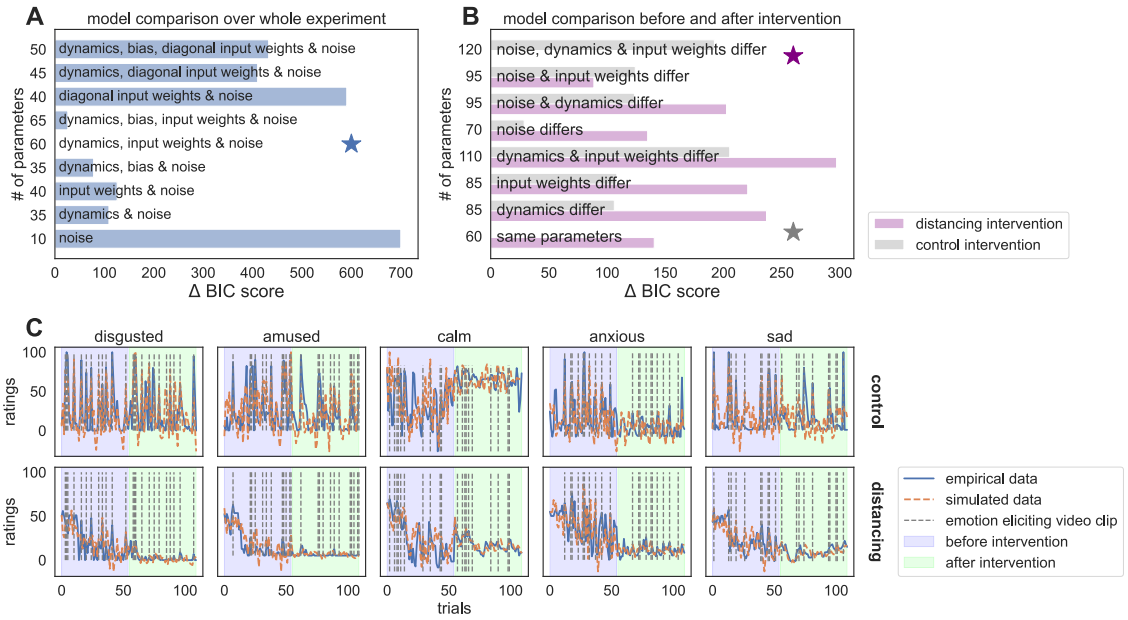

Figure 4: **Model Evaluation**. **A)** shows the differences in Bayesian Information Criterion (BIC) scores for all models tested compared to the most parsimonious model (blue star). All models were separately fitted to individuals' emotion rating time-series over the whole experiment. The left y-axis 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.

3.5 Effects of Distancing on Dynamics of Emotions

Next, we examined whether dynamics or the input weights or both were altered by the emotion regulation intervention (Fig. 4C). In the control intervention 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 emotion regulation 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 next examined the specific dynamical features that changed in response to the distancing intervention. Two participants had to be excluded as they were outliers in dynamical characteristics (cf. Supplementary Materials E Exclusion). The following analyses were hence based on 106 participants (55 randomized to the distancing intervention).

A linear dynamical system can be decomposed into eigenmodes – parallel, independent dynamical systems – using an eigendecomposition of the dynamics matrix $\mathbf{A}$ (cf. 2.4.2 Stability). Distancing altered the composition of the emotional eigenmodes ($T^2 = 14.77$, $F = 2.84$, $p = 0.019$; Fig. 5B). Examining the loadings on the individual emotion ratings, the first eigenvector of the dynamics matrix $\mathbf{A}$ pointed more towards calmness ($U = 1784, p = 0.01$; though this did not survive Bonferroni correction) and less towards sadness ($U = 1058, p = 0.02$; though this did not survive Bonferroni correction) in the distancing group when comparing groups after the intervention. This component was also more stable (decayed more slowly) in the distancing group ($U = 888, p = 0.001$; Fig. 5B). 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 $\mathbf{A}$ and the input weight matrix $\mathbf{C}$ 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. 2.4.3 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 $M = 331$, $SD = 283$, control group $M = 504$, $SD = 291$; $U = 884$, $p = 0.001$).

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 $\mathcal{C}$, which is based on a combination of dynamics and input matrices, $\mathbf{A}$ and $\mathbf{C}$. The eigenspace corresponding to the dominant eigenvalue of the controllability matrix, describing the most controllable direction, differed between the intervention groups after ($T^2 = 23.66$, $F = 4.55$, $p < 0.001$), but not before ($T^2 = 3.64$, $F = 0.7$, $p = 0.624$), the intervention (Fig. 5C).

A posthoc MANOVA revealed a significant interaction between time and intervention group on the most controllable direction ($F(5, 204) = 2.36$, $p = 0.0414$). Distancing altered which combination of emotions was most controllable (Fig. 5C), with combinations involving more calm ($U = 1917$, $p = 0.001$) and less sad emotions ($U = 825$, $p < 0.001$) being most controllable. This direction was, overall, less controllable (lower singular value; $U = 1988$, $p < 0.001$) in the emotion regulation group.

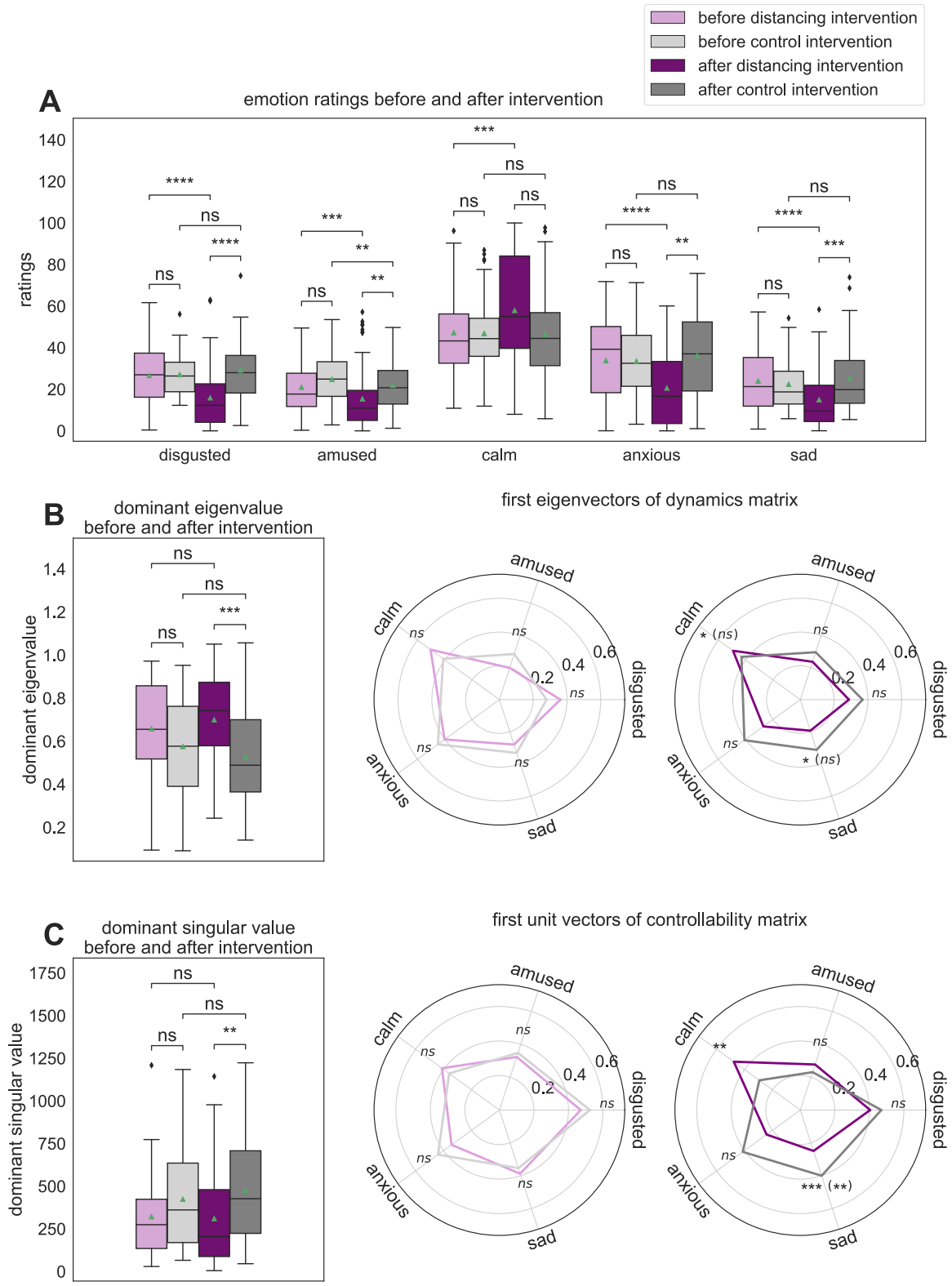

Figure 5: **Intervention Effects**. **A)** shows the ratings separated in before and after the intervention and for both intervention groups. *Continued on the next page*

Figure 5: 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 group-comparisons of the first eigenspaces of the dynamics matrix before and after the intervention. The boxplot to the left shows the distribution of the dominant eigenvalues. The polar plots to the right show the eigenvector direction of the dominant eigenvalue averaged across participants in either the distancing (purple shades) or the control (grey shades) group before (left) and after (right) the intervention. **C)** The boxplot illustrates the quartiles of the dominant singular values of the controllability matrix, with the whiskers showing the rest of the distribution. The polar plots on the right-hand side compare the unit vector direction of the dominant singular value 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. The significance in parenthesis reports the significance after Bonferroni correction for testing five different emotions.

3.7 Psychopathological correlates

The control of emotional states is thought to be altered in mental illness. To examine this, we acquired three psychological questionnaires measuring symptoms of depression (PHQ-9), generalized anxiety (GAD-7) and self-reported emotion regulation difficulties (DERS-18). The total scores of the three questionnaires were highly correlated ($r \in [0.69, 0.75]$, $p < 0.001$).

Self-reported success in complying with the intervention was related to the total DERS-18 score ($\beta = -0.3$, $p = 0.009$). The more difficulties participants reported in regulating their emotions, the less successful they thought they were in complying with the intervention. There was no significant interaction between DERS-18 score and intervention group in predicting emotion ratings ($\beta = 0.09$, $p = 0.7$).

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 $\beta < 0.12$, $p > 0.2$). 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 emotion ratings (all $p > 0.05$; cf. Supplementary Material Table 7).

Psychopathological symptoms were related to aspects of the dynamics of emotions. Difficulties in emotion regulation 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 ($\beta = 0.27, p = 0.005$), and away from amusement ($\beta = -0.27$, $p = 0.004$) and calmness ($\beta = -0.24$, $p = 0.012$; 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 ($\beta = 0.35$, $p < 0.001$).

There was no evidence for a link between symptoms and the extent to which the video clips altered the controllability or stability of emotions (all $p > 0.05$; cf. Supplementary Material

Table 9). Critically, there was no evidence that the symptoms moderated the effect of distancing (all $p > 0.05$; cf. Supplementary Material Table 8).

4 Discussion

Emotion regulation techniques are core components of psychotherapeutic approaches, effectively used to treat a number of different psychiatric conditions[14,12,57]. However, the underlying mechanism of psychotherapeutic effects remains unclear. By isolating a specific intervention component, i.e. emotion regulation, we aim to gain a deeper understanding of the processes involved in this specific treatment effect. To study emotions, we must consider that emotions fluctuate in intensity and frequency over time and might give rise to a complex dynamical system. By studying the dynamics of a particular individual, we hope to better understand how emotions change and how they respond to different interventions.

Here, we examined the impact of a well-characterized emotion regulation technique, namely distancing, on the dynamics of emotions over time. We did so in a setting where a complex multidimensional emotional state was elicited and altered over time using rich and powerful video stimuli. This allowed us, first, to establish a dynamical system account of how different emotions influence each other. Second, we were able to examine the relative impact of video clips on emotions and, finally, to disentangle the effect of distancing on the stability and controllability of a complex emotional state.

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 intricate interactions, and temporal dependencies[58,23,24,25,26]. Computational modelling results suggest that external inputs were important in explaining a higher dimensional affective state. 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' affective responses[48,47,59,46,60]. Omitting inputs in a study on 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.[49] has suggested 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.

Furthermore, emotional distancing intervention reliably reduced ratings and variability of both positive and negative emotions but increased ratings of calmness. As the multidimensional emotion states sequence was reasonably well-characterized as a simple linear dynamical system, we were able to examine the impact of distancing more formally. Model comparison revealed that a combination of dynamic and controllability signatures changed due to a distancing intervention. More precisely, a brief distancing intervention stabilized intrinsic emotional dynamics and reduced the impact of external stimuli. Additionally, distancing had an effect on the most controllable combination of emotions by enhancing calm and attenuating sad emotions relative to each other and the other emotions.

Psychopathology has been associated with deficits in cognitive control[61,62]. Distancing, however, is likely to involve several underlying cognitive control processes[14]. Processes such as

taking a step back from the situation, observing it objectively, and cognitively re-framing the experience to focus on its positive aspects instead of dwelling on the negative feelings are likely to require various aspects of cognitive control. These aspects may include inhibiting pre-potent evaluations, shifting attention away from external stimuli towards the self, and maintaining an intention to detach[14,63,64,65]. Indeed, high self-controllers are more successful in regulating emotions[66], self-control is related to emotional stability[67,68], and emotional *in*stability can be improved after self-control training[69]. One interesting considering is that cognitive biases might affect emotion regulation ability, thereby setting the stage for maintained negative affect and diminished levels of positive affect[70,71]. For example, individuals with depression may have difficulty inhibiting negative thoughts or shifting their attention away from negative stimuli. This can lead to a cycle of negative thinking, which can further worsen symptoms[72]. Psychotherapeutic intervention can improve cognitive control and help individuals with depression to develop strategies for regulating their thoughts and emotions[73,74].

As expected given the characteristically sustained negative affect and the difficulties experiencing positive affect[75] in depression, depressive and anxiety symptoms and emotion regulation difficulties were associated with average emotion ratings. Furthermore, subjectively reported difficulties in emotion regulation were linked to the controllability of specific emotions, i.e. disgust, amusement, and calmness. This might suggest that the variation of certain emotions is more intrinsically linked to participants' estimate of emotion regulation ability. Interestingly, amusement and disgust are the emotions more strongly linked to events[57,76]. However, the more specific prediction arising from the considerations around cognitive control, namely that symptoms of psychopathology should correlate with the efficacy of distancing, was not found.

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 time-series 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.

Third, one methodological detail is that emotion ratings and emotion stimulation were delivered concurrently. A better differentiation between stability and control could have been achieved with more frequent ratings and less frequent inputs.

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. We suggest that further computationally detailed characterization of emotional state dynamics may be useful on the path towards understanding differential and specific effects of different psychotherapeutic interventions.

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6 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.

7 Competing Interests

QJMH has obtained a research grant from Koa Health, and obtained fees and options for consultancies for Aya Technologies and Alto Neuroscience. JM reports no conflicts of interest.

8 Data Sharing Statement

Fully anonymised data and code for data analysis of this study will be available from a Github repository (https://github.com/huyslab/emotioncon) upon peer-reviewed publication.

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