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Citation

Pasteuning, J., Broeder, C., Sep, M., Elzinga, B. M., Penninx, B., Vinkers, C., & Giltay, E. (2025). Dynamic time warping to model daily life stress reactivity in a clinical and non-clinical sample: an ecological momentary assessment study. *Journal Of Affective Disorders*, *390*. doi:10.1016/j.jad.2025.119833

Version: Publisher's Version

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Downloaded from: https://hdl.handle.net/1887/4255277

Note: To cite this publication please use the final published version (if applicable).

Journal of Affective Disorders 390 (2025) 119833

Contents lists available at ScienceDirect

Journal of Affective Disorders

journal homepage: www.elsevier.com/locate/jad

Research paper

Dynamic time warping to model daily life stress reactivity in a clinical and non-clinical sample – An ecological momentary assessment study

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A R T I C L E I N F O

Keywords:
Dynamic time warping
Ecological momentary assessment
Affective disorders
Stress reactivity
Emotional responsivity

A B S T R A C T

Background: Dysregulated stress reactivity has been closely linked to psychopathology. However, most studies have applied cross-sectional lab-based methodologies rather than longitudinal designs, like ecological momentary assessment (EMA). EMA provides dynamic, time-sensitive data that require advanced analytical approaches. Dynamic time warping (DTW) is particularly suited for capturing the temporal dynamics between EMA-items.
Methods: We applied DTW to examine daily life stress reactivity in 99 participants with a current affective disorder and 277 controls. Using EMA-data, we assessed emotional reactivity to social stressors (i.e., unpleasant or missing company), event-related stressors (i.e., unpleasant experiences), and positive events (i.e., pleasant company or experiences). DTW distances between affect items, stressors, and positive events were calculated to construct group-level networks reflecting undirected and temporal relationships.
Results: The current affective disorder group reported more unpleasant and fewer pleasant events compared to controls, rated their company as pleasant less often, and reported missing company more frequently. In undirected analyses, they showed strong connections between positive and negative emotions, while these formed distinct clusters in controls. Accordingly, temporal network analyses revealed stronger emotional responses to stressors in the affective disorder group. Additionally, unpleasant and pleasant experiences significantly preceded emotional changes in this group but not in controls.
Conclusion: Our findings highlight heightened reactivity to daily events in individuals with a current affective disorder. We demonstrate an application of DTW in psychiatry research and showcase its ability to analyze complex time-series data, infer causality, and create directional networks at the item level for a more in-depth study of stress reactivity.

1. Introduction

The stress response is an adaptive process essential for maintaining homeostasis. However, when stressors become frequent or chronic, they can disrupt physiological and psychological processes that ensure an adequate stress response (De Kloet et al., 2005). As such, disrupted stress reactivity may increase the vulnerability for stress to become pathogenic. Indeed, dysregulated reactivity to stressors has been linked to the onset, maintenance, and exacerbation of psychopathology, particularly major depressive disorder (MDD) and anxiety disorders (McEwen, 2004;

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https://doi.org/10.1016/j.jad.2025.119833
Received 28 February 2025; Received in revised form 26 June 2025; Accepted 2 July 2025
Available online 4 July 2025
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Vinkers et al., 2021). Recent efforts have tried to uncover the underlying mechanisms of dysregulated stress reactivity and sensitization in people with such psychopathology, but have mainly done so using cross-sectional lab-based methodologies. Such conventional methods typically include retrospective questionnaires on stressful events introducing recall bias, especially regarding negative mood states that are particularly relevant to the study of the effects of stressors (Sato and Kawahara, 2011; Spinhoven et al., 2011a; Talari and Goyal, 2020). Therefore, longitudinal designs incorporated into daily life are of particular interest in studying stress reactivity, due to the wealth of data and higher ecological validity that they generate (Shiffman et al., 2008).

One way to adopt such a method is to operationalize stress reactivity in terms of affect fluctuations and assess these in everyday life using ecological momentary assessment (EMA). EMA involves repeated sampling of subjects' behaviors, emotions, and experiences. Typically, participants fill out the EMA-questionnaires using their smartphone, which generally only takes a few minutes. Therefore, participants can continue their daily activities, hence the term ecological. A major limitation to current EMA-studies, however, is that they have largely disregarded context (i.e., situational information) when assessing participants' emotional experiences (Dejonckheere et al., 2019). This is unfortunate, because it only captures the stress response while neglecting the stressor, omitting critical information. For instance, recent evidence that did take stressors into account suggests that it takes longer for negative affect (NA) to return to its baseline level following the first stressful event of a given day in individuals at risk for depression (Velozo et al., 2023). Importantly, cumulative stressors, but not stressor intensity, was associated with such slower affective stress recovery. In addition, EMA-based studies have shown increased instability and variability in day-to-day affect fluctuations in patients with a current affective disorder in comparison to patients with a remitted disorder or no diagnosis (Schoevers et al., 2021; Seidl et al., 2023). While increased affect instability and variability could lead to more sensitivity to internal and external stressors, reporting on daily life stressors remains limited. By combining affect fluctuations with contextual information we aim to use EMA-data more optimally and yield more extensive information on daily life stress reactivity.

Analyzing longitudinal time-series data, however, is inherently complex, and requires an approach that is time-sensitive and dynamic. A recently introduced statistical algorithm in psychological and psychiatric research, dynamic time warping (DTW; de Beurs et al., 2024; Hebbrecht et al., 2020; Mesbah et al., 2023; van den Brink et al., 2024; van der Does et al., 2023; van der Slot et al., 2024), could be well-suited to analyze affect fluctuations in response to stressors using EMA-data. DTW is a technique used to determine the best shape-based alignment between two sequences that change over time. It achieves this by measuring the distance that needs to be bridged between the two time series for these to overlap through dynamic stretching and contraction. While other methods, such as vector autoregressive (VAR) and group iterative multiple model estimation (GIMME) modeling, have been successfully used in network analysis, they rely on assumptions of stationarity and equal time intervals between data points (Bringmann et al., 2022; Jordan et al., 2020), which are often not met in EMA-research. As such, the non-linear DTW method might be a more suitable approach, as it enables the examination of temporal dynamics between items, such as stressors and both negative and positive affect (PA) items, across various time points. Unlike value-based methods, such as VAR, DTW is shape-based and aligns trajectories based on their overall patterns, allowing for meaningful comparisons even when data points are unequally spaced, as is often the case in EMA research (van der Does et al., 2025). Undirected DTW captures whether the patterns of item scores exhibit similar temporal dynamics, showing simultaneous increases or decreases. Furthermore, directed DTW analysis enables the evaluation of temporal order, revealing whether an increase in one item's score is followed by an increase or decrease in other items' scores. As such, stronger hypotheses surrounding temporal order (i.e., Granger causality) can be made on data with a high ecological validity (Shiffman et al., 2008). These advantages make DTW a particularly suitable method to analyze dynamics between affect and stressor items in repeated measures data such as EMA. However, to our knowledge, no studies to date have incorporated these three elements (i.e., DTW, EMA, and stressor [context]).

Therefore, we will use DTW as a promising tool to capture detailed evidence on daily life stress reactivity and evaluate its benefits. In addition, we will evaluate emotional reactivity to positive events, to provide an even better representation of affect fluctuations in the context of stress. We will do so using real-life EMA-data from a sample including individuals with a current affective disorder, as well as healthy controls.

2. Methods

2.1. Sample

The sample existed of 384 participants (aged 18–65 years) from the Netherlands Study of Depression and Anxiety (NESDA) cohort, an ongoing longitudinal multi-site cohort study aimed at determining the development and long-term course of depression and anxiety (Penninx et al., 2021). Individuals with MDD and anxiety disorders (i.e., current affective disorder), as well as without any current affective disorder (i.e., controls) were included. During the sixth wave of NESDA, a 2-week EMA & Actigraphy (NESDA-EMAA) sub-study was carried out. Here, only EMA-data collected during this sixth wave has been included. Diagnoses were confirmed with the Composite International Diagnostic Interview (CIDI, version 2.1; Wittchen, 1994) 6 months before the start of the EMA-period.

NESDA, including the EMAA sub-study, was approved by the VUmc ethical committee and all participants gave informed consent. Similar to Servaas et al. (2017) and Schoevers et al. (2021), all participants with a response rate above 50 % were included in the analysis, resulting in a total sample size of 376 (97.9 %).

2.2. Ecological momentary assessment

EMA-assessments were conducted using a secured server system (RoQua, Sytema and van der Krieke, 2013), as described by Schoevers et al. (2021) (among others, e.g., van Genugten et al., 2020). The software sent texts to participants' smartphones, containing links to online questionnaires. Assessment's time intervals were personalized to the participants' circadian rhythms. The assessments took place for 2 weeks, with 5 assessments per day, sorted in a fixed design of one assessment per 3 h, resulting in equal time intervals between assessments within a single day but larger temporal lags between the last assessment of one day and the first of the next day. If participants did not respond to the questionnaires within 30 min, they received a reminder to complete them. Participants had up to one hour to complete the questionnaire, after that the entry point was registered as missing. During the assessment period, research assistants called the participants twice (24 h and 1 week after they had started EMA) to ask whether they had questions and to motivate them to continue filling out the questionnaires.

2.3. Measurements

2.3.1. Stressors

We investigated two types of daily life stressors, as previously described by Myin-Germeys et al. (2001). They are defined as follows.

Event-related stressors were calculated based on whether a participant had had an unpleasant experience since he or she had filled out the previous assessment. The participants could rate the most important recent unpleasant event: 'how unpleasant was this experience?' and 'how important was this unpleasant experience?'. Both items were answered on a 7-point Likert scale, ranging from 1 = 'not unpleasant' to

7 = 'very unpleasant' and 1 = 'not important' to 7 = 'very important', respectively. The event-related stressor score, quantified as unpleasant experience, was calculated as the average score on these two items.

Social stressors were based on the question 'with whom are you at the moment?'. If subjects answered this item with 'in company of others', they were asked to rate how they experience their company on a 7-point Likert-scale ranging from 1 = 'very bad' to 7 = 'very good'. The social stressor score, quantified as 'unpleasant company', was calculated as the reversed score on this item for score 1, 2, and 3; while scores of 4 through 7 were set to zero. Additionally, it was considered whether participants were missing company. When subjects answered the question 'with who are you at the moment?' with 'alone', they were asked whether they would have rather been in company, which they could answer on a 7-point Likert-scale ranging from 1 = 'not at all' to 7 = 'very much'.

2.3.2. Positive events

In addition to the negative events that constitute the stressors, we investigated positive events. They are defined as follows.

Pleasant experiences were defined based on similar items to unpleasant experiences, which were asked when participants indicated they experienced something pleasant: 'how pleasant was this experience?' and 'how important was this pleasant experience?'. Both items were answered on a 7-point Likert-scale, ranging from 1 = 'not pleasant' to 7 = 'very pleasant' and 1 = 'not important' to 7 = 'very important', respectively. Pleasant experience was defined as the average score on these two items.

Pleasant company was also based on the question 'with whom are you at the moment?'. If subjects answered this item with 'in company of others', they were asked to rate how they experience their company on a 7-point Likert-scale ranging from 1 = 'very bad' to 7 = 'very good'. Pleasant company was then defined as the (unreversed) score; where scores of 5, 6, and 7 were recoded as 1,2 and 3, respectively; while scores of 1 through 4 were set to zero.

2.4. Positive and negative affect

The EMA-questionnaires included a total of 16 items assessing both positive and negative affect. For the current study, affect items that were previously used by Schoevers et al. (2021) were selected that cover emotional adjectives on the positive and negative valence dimension as well as the high and low arousal dimension of emotional experience, resulting in a total of 13 items. These included six positive affect items: I feel satisfied, relaxed, cheerful, energetic, enthusiastic, and calm; and seven negative affect items: I feel upset, irritated, apathic, down, nervous, bored, and anxious. All items were rated on a 7-point Likert-scale, ranging from 1 = 'not at all' to 7 = 'very much'.

2.5. Statistical analysis

DTW is based on the concept of a warping curve, which stretches two given time series so that they align. To align these time series, a distance has to be covered, with a greater final distance for item pairs that show more dissimilar trajectories over time. We conducted two types of DTW analyses: undirected, which measures similarity in time series without temporal direction, and directed, which identifies (potential causal) precedence between item scores over time. Both analyses result in network plots, one for undirected, and the other for directed item relationships. In addition, we assessed the standardized in- and out-strength centrality of each item in the directed networks, which indicates whether changes in an item's score precede changes in other item scores (i.e., greater out-strength or temporal lead) or follow changes in other items (i.e., greater in-strength or temporal lag). These centrality measures reflect the relative potential influence each variable has on the other variables within the network (i.e., Granger causality; Granger, 1969). Each of these steps helps to capture different aspects of the dynamic interactions over time among all the included variables. All affect items, stressors, and positive events were group-level standardized before the DTW analyses to ensure that outcomes were based on relative changes in item scores over time, allowing for a meaningful comparison of trajectories even when scores fluctuated with different mean severity levels between individuals.

First, for the undirected DTW analysis, a distance matrix was computed for each participant based on their time series data. In doing so, certain constraints were applied. Specifically, we chose a symmetric Sakoe-Chiba window type of one, which allowed us to look at relations between items within a more narrow window, both forward and backward in time. In addition, we used a 'symmetric2' step pattern, which permits flexible alignment steps (diagonal, vertical, and horizontal) while enabling normalization of distances for the number of observations per participant. This ensures that overall distance values are comparable across individuals with differing lengths in time series (Fig. 1F). The analysis resulted in a symmetric distance matrix, with an equal distance from item A to item B as from item B to item A. Based on the distance matrix, a network plot was generated for each group to visually represent the dynamic correlations between stressors and other variables. In this plot, the thickness of the edges corresponds to the strength of the association and reflects the distances that are significantly smaller ($p < .05$) than the average of all remaining distances. Notably, this significance testing was performed separately within each group's network, meaning that relatively smaller distances are shown in comparison to all other distances within that network. Therefore, undirected edge strength comparisons are valid only within a group and not between groups.

Subsequently, a directed DTW analysis was conducted using the same DTW algorithm as for the undirected analysis, but with a crucial modification: the Sakoe-Chiba window type of one was specified as asymmetric, in contrast to the symmetric window type used for the undirected analysis. This specification ensured that only unidirectional dynamic alignment was allowed, specifically towards a point occurring later in time. As in the undirected analysis, a 'symmetric2' step pattern was used. To illustrate how this works, consider Fig. 1 as an example and assume the (unstandardized) scores for an item 17 (i.e., unpleasant experience) and an item 10 (i.e., feeling down) from one participant over the course of 10 time points (Fig. 1A and B). Please note that the data shown are synthetic and used solely for illustrative purposes, based on realistic values that are commonly observed in our data; the figure does not reflect the actual sampling schedule used in the study. First, DTW creates a local cost matrix (LCM) with t x t dimensions (here, 10 timepoints × 10 timepoints, as shown in Fig. 1C and D). Alongside the axes of each LCM, the scores of item 17 and 10 are shown, as previously depicted in panel A and B. Each cell in the matrix then shows the cost (i.e., distance) of aligning the score of items 10 and 17 at a pair of time points. Because of the current window of one, only entries for those cells falling within this window are shown. Second, DTW finds the path that minimizes the alignment between the two scores by iteratively stepping through the LCM, starting at the lower left corner (i.e., LCM[1,1]) and finishing at the upper right corner (i.e., LCM[10,10]), while aggregating the total distance (i.e., 'cost' = distance). At each step, the algorithm takes the step in the direction in which the cost increases the least under the chosen constraint (i.e., asymmetric window of size one, with a 'symmetric2' step pattern). To yield directed distances, the stretching is only allowed in one direction, from one assessment at a given timepoint to another at the following timepoint. Panel C visually represents the alignment process from item 17 to item 10, while panel D represents aligning item 10 to item 17. In the yellow boxes (panel E), the calculation of the directed distance is explained, which is the relative difference between the two calculated final distances (from panel C and D) divided by their sum. This directed distance can vary between −1 and + 1, where +1 would indicate that the trajectory of one item is exactly mimicked by the other item one time point later. In other words, values near +1 indicate that changes in one item are consistently followed by

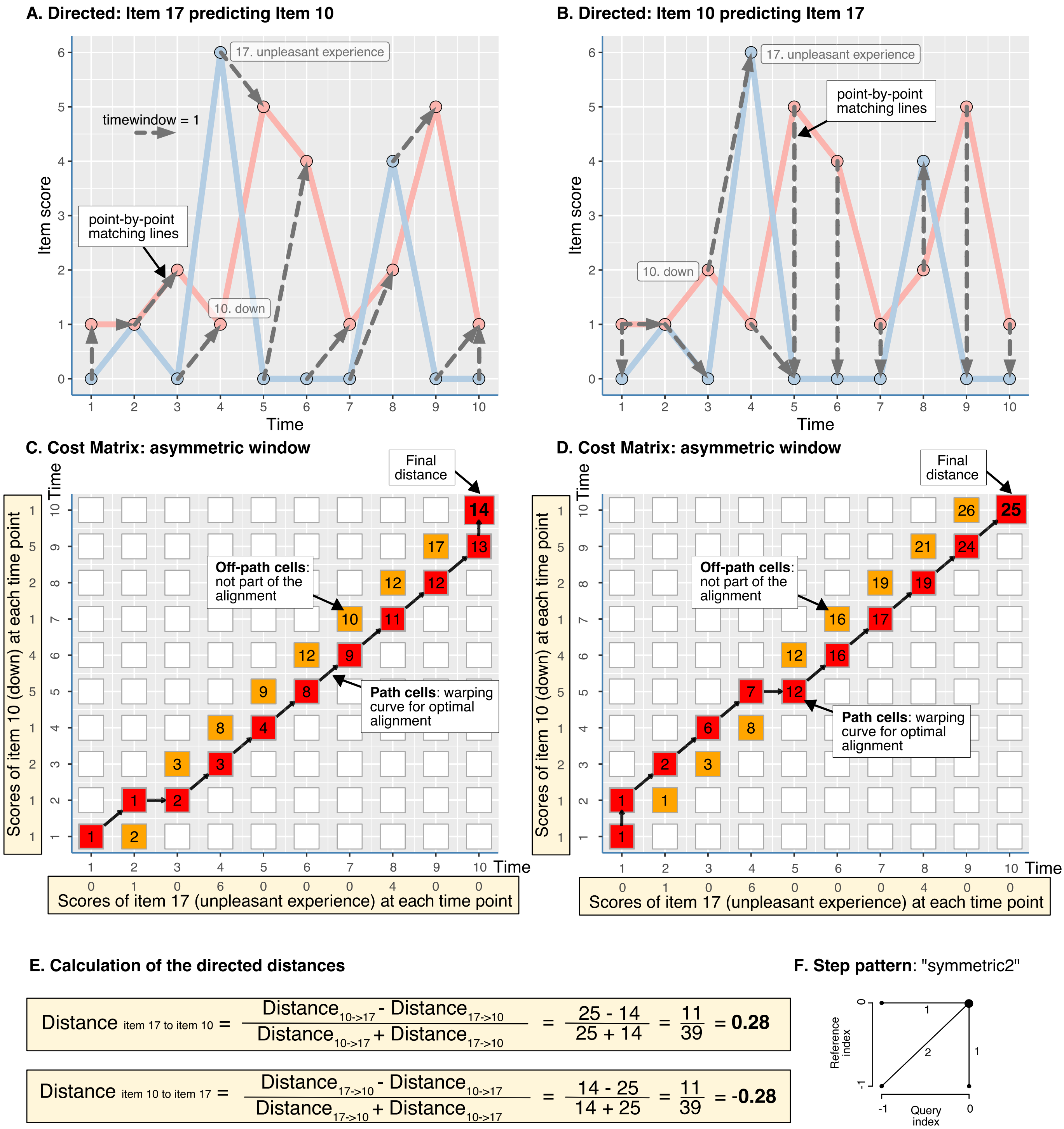

Fig. 1. Explanation of a DTW analysis. Please note: data shown are synthetic and used solely for illustrative purposes, based on realistic values that are commonly observed in our data; the figure does not reflect the actual sampling schedule used in the study. A) The directed distance between the (unstandardized) score of item 17 (unpleasant experience; blue line) predicting the score of item 10 (feeling down; red line) across ten timepoints (t) within one participant. B) The directed distance between the (unstandardized) score of item 10 (unpleasant experience; blue line) predicting the score of item 17 (feeling down; red line) across ten timepoints (t) within one participant. C) The t x t cost matrix of item 17 to item 10 for the same participant. The numbers on the x- and y-axis represent item scores. The red boxes indicate the (shortest) path with the lowest cost. The orange boxes indicate alternative paths with a higher cost. Here, the option was to warp below the diagonal. D) The t x t cost matrix of item 10 to item 17 for the same participant. Here, the option was to warp above the diagonal. E) The calculation of the directed distances for both item 17 to item 10 and item 10 to item 17. F) The symmetric step pattern used in the analysis, allowing distances to be normalized for the number of assessments per participant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

changes in the other item at the next timepoint. In contrast, values near −1 indicate that changes in one item consistently follow changes in the other item at the previous timepoint. A directed distance of 0 would indicate that both trajectories have exactly the same shape. In our example case, we yield a directed distance score of 0.28 for the direction of item 17 to 10, and a score of −0.28 for item 10 to 17. Based on these example scores, we can conclude that changes in unpleasant experiences (item 17) tend to precede changes in feeling down (item 10) in this individual. To promote transparency and reproducibility, the sample code is given on Open Science Framework via OSF | Simulation code.R (https://osf.io/hb4xn or https://osf.io/fx8y5).

Finally, the distance matrices of all participants were combined and the mean and 95 % CI confidence intervals of the directed in- and out-strength were assessed. The latter confidence intervals were assessed through bootstrapping (5000 times). While instrength centrality represents the sum of weights of the ingoing edges (i.e., connections), out-strength centrality represents the sum of weights of the outgoing edges. The “dtw” (version 1.23–1), “parallelDist” (version 0.2.9), and “qgraph” (version 1.9.6) packages were employed for the DTW and network analyses using R statistical software (v4.2.2; R Core Team, 2020). In addition, the “lme4” package (version 1.1–30; Bates et al., 2015) was used to run linear mixed-effects models to assess group differences in EMA-item scores, accounting for multiple distance measures within participants.

3. Results

3.1. Demographics

A total of 376 participants were included, of whom 99 had a current affective disorder and 277 did not. Of participants with a current affective disorder, 42 had an MDD diagnosis, 10 a general anxiety disorder (GAD) diagnosis, and 52 another anxiety disorder diagnosis, including social phobia, agoraphobia, and panic disorder with and without agoraphobia. Demographic characteristics are provided in Table 1. The groups did not differ significantly in sex, age, education, smoking, BMI, and alcohol use. The current affective disorder group reported significantly more unpleasant events (7.6 %) as compared to the control group (5.9 %), as well as significantly less pleasant events (23.4 %) as compared to controls (28.6 %), but reported more experiences of both unpleasant and pleasant events since the previous assessment (7.9 %, controls: 5.7 %). The control group indicated to be in company of others more often (70.3 %) as compared to the current disorder group (64.8 %). Additionally, the current affective disorder group more often rated their company as unpleasant as compared to controls (3.6 %, controls: 2.0 %), while the majority of the time company was still rated as pleasant (81.5 %, controls: 89.1 %). Between groups, fewer people indicated to not miss company at all in the current disorder group (42.2 %) as compared to controls (50.6 %). In the same vein, the current disorder group indicated more frequently to preferred having been in company a little to moderately (rated 2–4 on a 7-point Likert scale; 43.5 %) as well as moderately to a lot (rated 5–7; 14.2 %) as compared to controls (36.2 %; 13.1 %). Supplementary Table 1 shows more detailed information on EMA-reports, including type of events and experiences.

3.2. DTW analysis

DTW analysis of the affect, stressor and positive event items showed temporal patterns of covariation between items and a network per group that displays these patterns.

The undirected networks are displayed in Figs. 2A and 3A. Since the significance of the edges within the undirected networks is calculated separately within each group, it cannot be directly compared between the two networks. However, important differences are evident: in the current affective disorder group, the negative valence mood items show more negative connections with the positive valence items as one big cluster of mood items, whereas in the control group two clusters emerged; the negative valence items were more interconnected with one another as a separate cluster, similar to the positive valence items.

Table 1
Demographic characteristics. BMI = body mass index. MDD = major depressive disorder. gAD = general anxiety disorder. Other diagnoses include social phobia, agoraphobia, and panic disorder with and without agoraphobia. AUDIT = alcohol use disorders identification test where ≥8 indicates hazardous drinking and >15 indicates likelihood of alcohol dependence (moderate-severe alcohol use disorder). IDS = Inventory of Depressive Symptomatology. BAI = Beck's Anxiety Index. An asterisk indicates significance.

	Controls (n = 277)	Current affective disorder (n = 99)	p-Value
Female sex	185 (66.8 %)	63 (63.6 %)	0.57
Age (years)	49.6 ± 12.9	49.9 ± 11.4	0.83
Education (in years)	13.11 ± 2.88	12.59 ± 3.47	0.15
Smoking (yes)	59 (21.3 %)	27 (27.4 %)	0.25
BMI	25.4 ± 5.1	25.8 ± 5.0	0.45
Alcohol use (AUDIT)	4.39 ± 4.56	5.11 ± 6.72	0.24
MDD/GAD/Other diagnosis	0/0/0	42/10/52	–
IDS	10.32 ± 8.21	25.08 ± 13.35	<0.001*
BAI	4.47 ± 5.19	13.55 ± 10.44	<0.001*
Fear questionnaire	10.43 ± 11.90	24.73 ± 20.15	<0.001*
Mean PA score	5.03 ± 1.29	4.15 ± 1.37	<0.001*
Mean NA score	1.39 ± 0.95	2.16 ± 1.46	<0.001*
Frequencies of stressors and positive events			
Unpleasant experience	5.9 %	7.6 %	<0.001*
Pleasant experience	28.6 %	23.4 %	<0.001*
Both unpleasant and pleasant experience	5.7 %	7.9 %	<0.001*
Time spent in company	70.3 %	64.8 %	<0.001*
Unpleasant company	2.0 %	3.6 %	<0.001*
Pleasant company	89.1 %	81.5 %	<0.001*
Missing company			
1 (not at all)	50.6 %	42.2 %	<0.001*
2	13.5 %	18.9 %	<0.001*
3	7.7 %	12.8 %	<0.001*
4	15.0 %	11.8 %	<0.001*
5	7.3 %	8.5 %	0.07
6	3.5 %	4.9 %	0.005*
7 (very much)	2.3 %	0.8 %	<0.001*

The directed networks are displayed in Figs. 2B and 3B. Here, edge thickness and color intensity can be directly compared among the two figures, as these reflect the strength of the directed distances. Overall, the directed network of the current affective disorder group showed stronger connections between all items (Fig. 3B), as displayed by thicker arrows, compared to the control group (Fig. 2B). Specifically, event-related stress (i.e., unpleasant experiences) had a strong effect on both PA and NA items in this group, including feeling satisfied, listless/apathic, down, and anxious. In addition, event-related stress significantly affected missing company. These effects were not found, or to a much lesser extent, in controls. These findings were further confirmed by significant outstrength of unpleasant experience in the current affective disorder group, but not in controls. Furthermore, significant instrength of feeling satisfied was found in both groups. While feeling cheerful showed significant instrength in the control group, it showed significant outstrength in the current affective disorder group. Lastly, feeling energetic and enthusiastic were found to more strongly affect other items in the control network than in the current affective disorder network, as shown by significant outstrength.

To facilitate clearer comparison of the most relevant associations, Fig. 4A and B show only the significant edges between affect items and the five stressors and positive events (yellow nodes) for both groups, omitting edges among the affect items or among the stressors and positive events. As with Figs. 2B and 3B, the edge thickness and color intensity can be directly compared among the two networks. Furthermore, both unpleasant and pleasant experience showed a significant

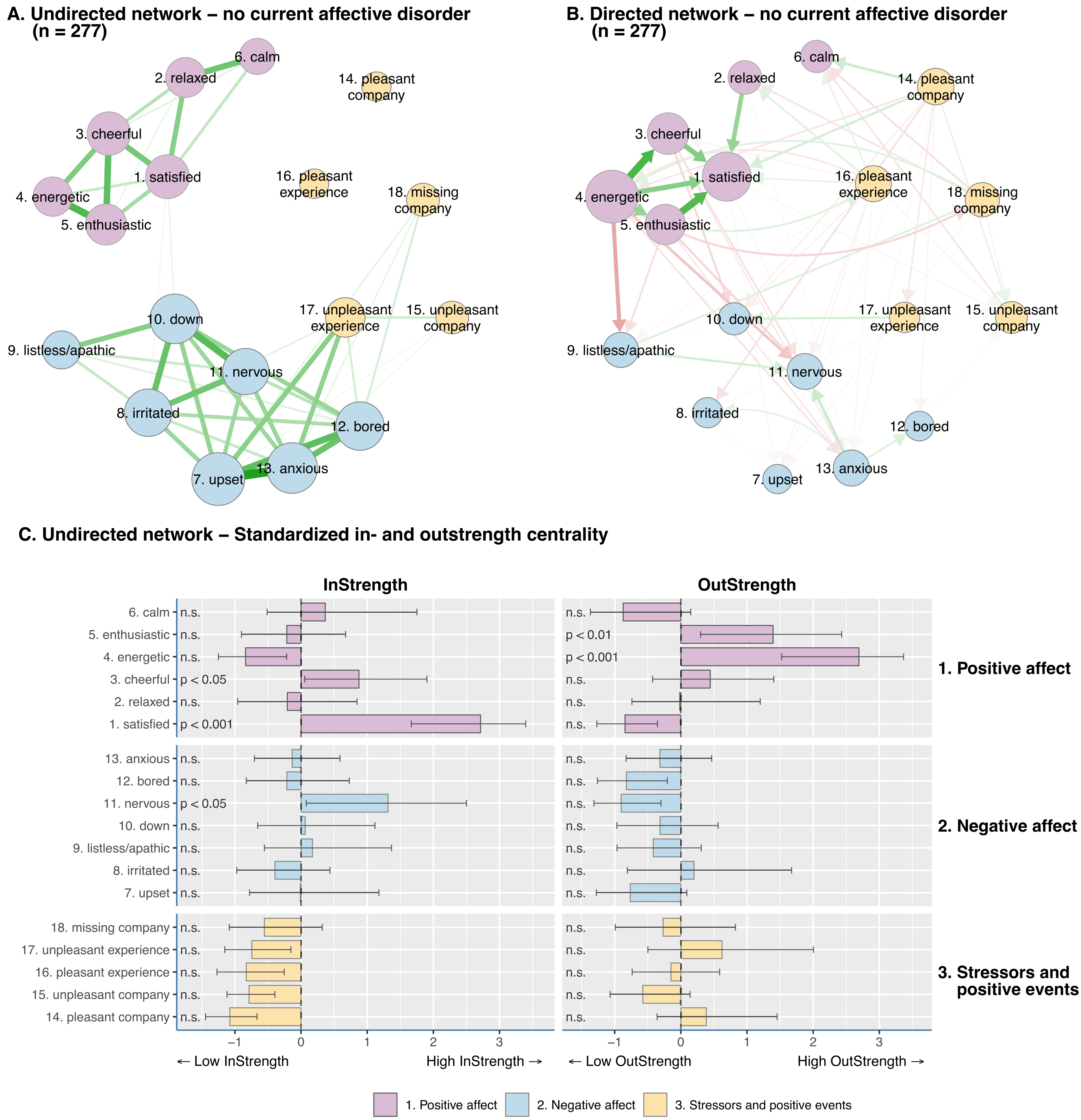

Fig. 2. Dynamic time warping and centrality analyses for the control group. A) The undirected network of the control group. Higher thickness of edges represents higher strength. Red indicates a negative relationship, while green indicates a positive one. B) The directed network of the control group. Arrows indicate the direction of the effect. C) Standardized in- and outstrength centrality of positive and negative affect and stressors and counterparts for the control group. n.s. = not significant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

outstrength centrality index for the current affective disorder group when directly compared to controls (Fig. 4C).

In addition, Supplementary Fig. 1 shows the standardized edge strengths compared between the two groups of only the significant arrows depicted in Fig. 4. The strength of these effects is the inverse of the distance. The results demonstrate that the temporal relationships between stressors and positive events (particularly pleasant and unpleasant experiences) and affect are consistently stronger in those with a current disorder than in controls. This figure further illustrates that people with a current affective disorder experience more intense emotional responses to both positive and negative experiences in daily life.

4. Discussion

In this study, we employed DTW to capture the dynamics of daily life stress reactivity in individuals with a current affective disorder and those without. The analysis revealed distinct relationships between

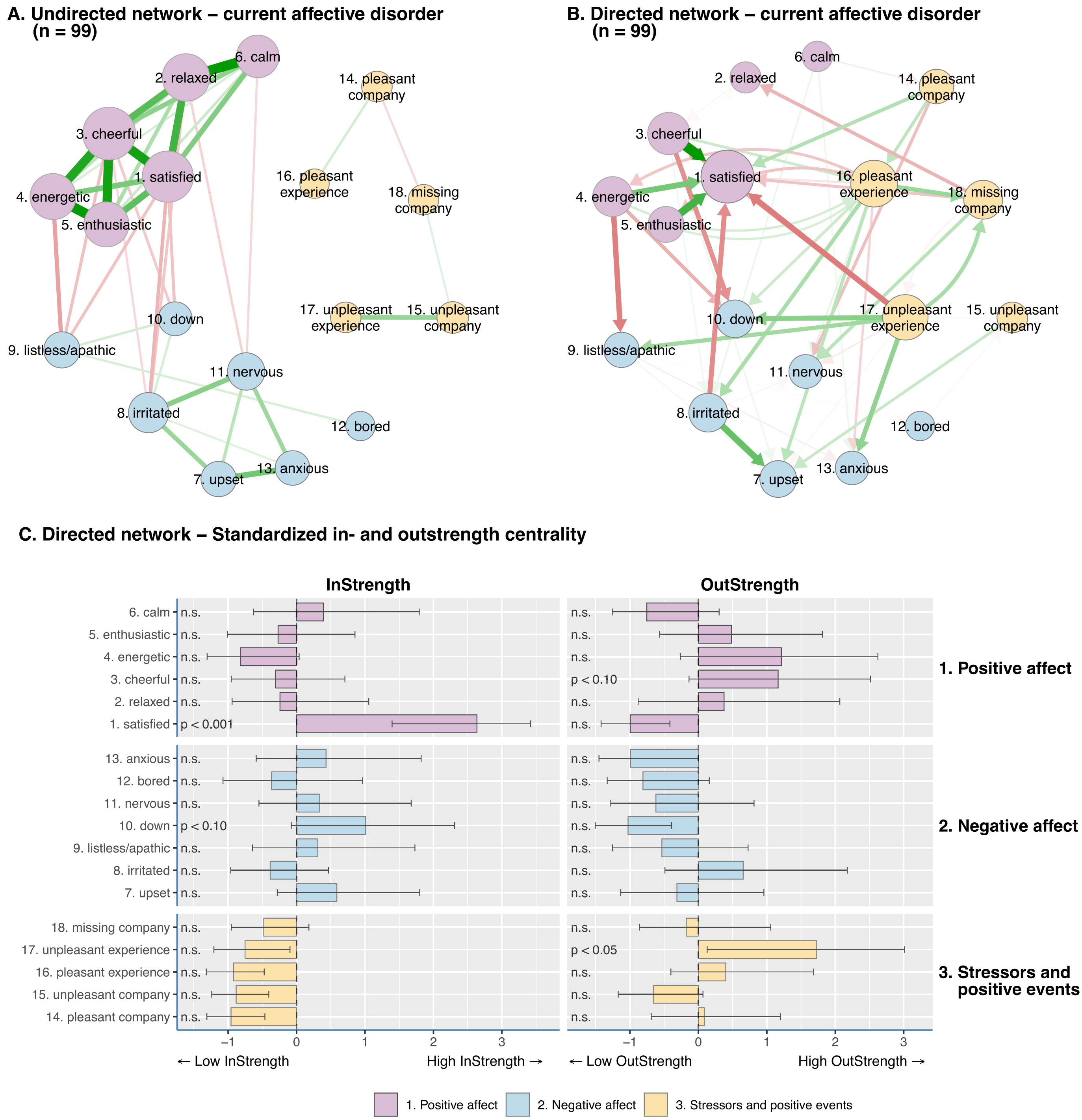

Fig. 3. Dynamic time warping and centrality analyses for the current affective disorder group. A) The undirected network of the current affective disorder group. Higher thickness of edges represents higher strength. Red indicates a negative relationship, while green indicates a positive one. B) The directed network of the current affective disorder group. Arrows indicate the direction of the effect. C) Standardized in- and outstrength centrality of positive and negative affect and stressors and counterparts for the current affective disorder group. n.s. = not significant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

stressors, positive events, and affect depending on psychopathology. Specifically, stronger connections between stressors and affect items were found for the current affective disorder group as compared to the control group. Notably, DTW provided insights into the temporal nature of these relationships, revealing that certain stressors and positive events preceded changes in affect. This method also allowed us to conduct network analyses, including in- and out-strength centrality measures, revealing that particularly unpleasant and pleasant experiences had greater emotional impact in those with a current affective disorder.

By using DTW, we gained valuable insight into daily stress reactivity across individuals with and without psychiatric disorders, introducing several advantages. Firstly, as previously mentioned, DTW can overcome certain limitations posed by other methods. For instance, VAR-based models (Bringmann et al., 2022) assume data stationarity, which is often violated in the context of clinical time-series data (Jordan

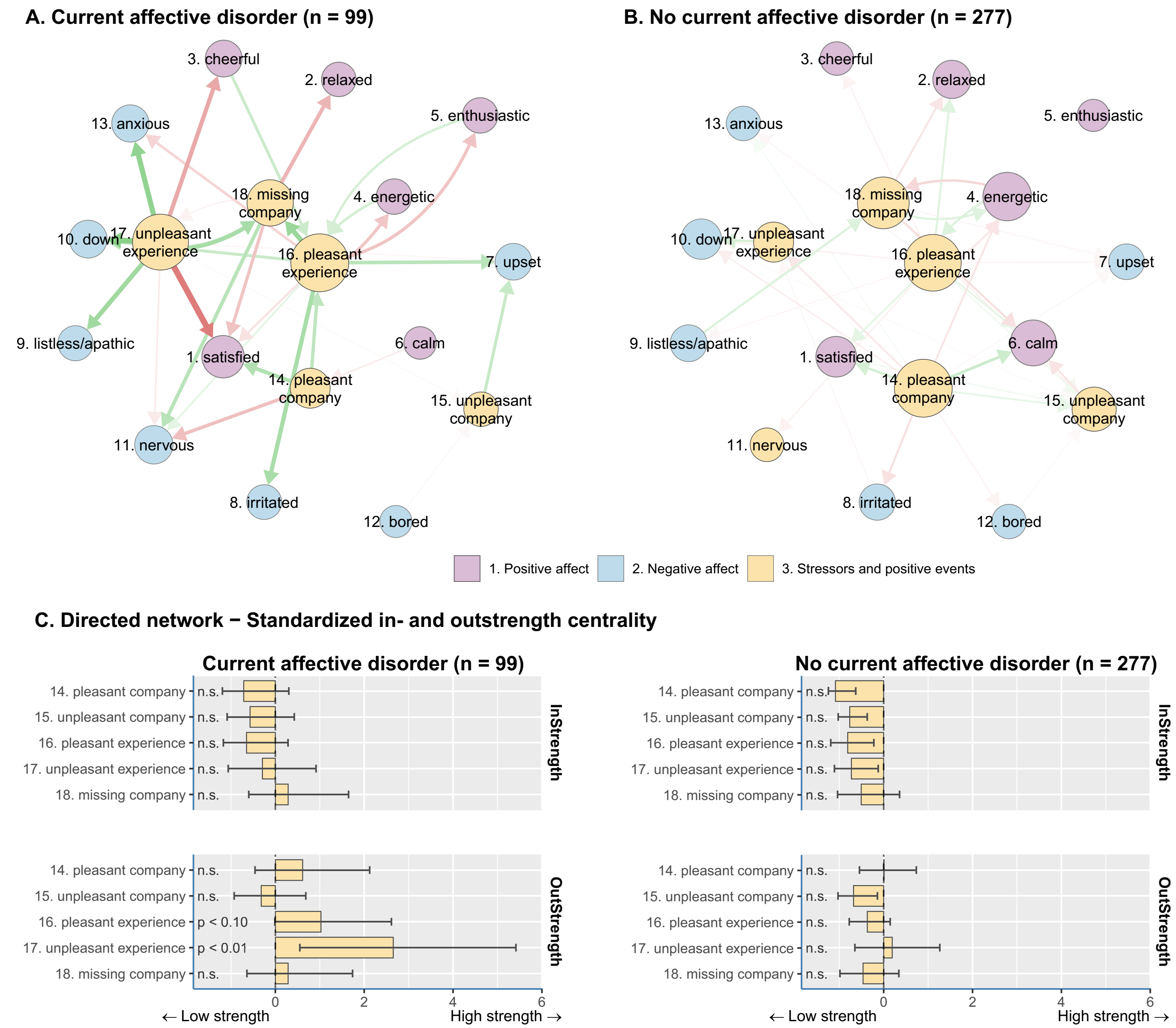

Fig. 4. Significant edges comparison of dynamic time warping analysis and their standardized in- and outstrength centrality. A) The directed network of the current affective disorder group, showing only significant edges. Arrows indicate the direction of the effect. Red indicates a negative relationship, while green indicates a positive one. B) The directed network of the control group, showing only significant edges. C) A comparison of standardized in- and outstrength centrality of stressors and counterparts. Variables that show significant strength centrality are found to be significant as compared to the other group. n.s. = not significant. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

et al., 2020). While alternative solutions to this problem exist (e.g., detrending), they may introduce new issues that may reduce the explanatory power of the model (Wu et al., 2007). Thus, using a method that is affected to a lesser extent by non-stationarity increases the overall reliability of the model. Similarly, DTW does not assume equal time intervals between observations, unlike VAR-based models. This makes it particularly well-suited for EMA data, where irregular gaps, such as overnight intervals, naturally occur. Secondly, while traditional methods are valuable, they may struggle with the temporal complexity of EMA-data, where many time points correlate with one another. DTW, however, allows for a more grounded hypothesis of causality, as it enables to account for temporal lag relationships. For instance, we observed that event-related stress preceded greater negative affect (e.g., down and anxious) and lower positive affect (e.g., satisfied) in the current disorder group but not (as much) in controls, better clarifying the effects of stressors and potential causality of affect. Thirdly, DTW allowed for undirected and directed networks, incorporating all items individually, rather than collapsing multiple items into general PA and NA scores, as is common in many EMA-studies. Analyzing items at this level of granularity provides a more nuanced understanding of individual item interactions. For example, in the current affective disorder network, we identified that unpleasant experiences substantially influenced feeling satisfied and down, but less so feeling upset and nervous. Additionally, while linear models tend to smooth out fluctuations in individual item scores throughout the day, DTW allows us to examine the finer details of daily stress reactivity, which are particularly relevant for understanding real-life stress responses.

Beyond methodological advantages, our findings align with research indicating dysregulated stress reactivity in affective disorders (McEwen, 2004; Spinhoven et al., 2011a, 2011b; Vinkers et al., 2021). We indeed observed a larger impact of stressors on affect in people with a current affective disorder, possibly due to a less stable affect network compared to controls. Supporting this view, Cramer et al. (2016), found that individuals at risk of developing depression often exhibit stronger connections between symptoms. In such tightly connected networks, a small perturbation may result in a large effect. Such dynamics point to the vulnerability of the affect network of individuals with affective disorders, where stressors act as perturbations that influence emotional fluctuations more strongly. Consistent with this interpretation, our directed DTW analyses revealed more temporal associations between stressors, particularly unpleasant experience, and negative affect in the affective disorder group. However, undirected analyses showed weaker connections, suggesting heightened reactivity, but reduced overall temporal consistency or synchrony. Conversely, in healthy individuals, undirected analyses revealed correlations between negative affect and stressors, while directed analyses showed fewer temporal links. This may indicate a more stable and loosely connected network, in which affect and daily events co-fluctuate in a regulated manner, helping to buffer the effect of perturbations and maintain homeostasis. In those with psychopathology, this buffering capacity may be compromised. This finding aligns with hierarchical control systems and active inference frameworks, where predictive mechanisms regulate affect. Here, heightened stress sensitivity stems from an impaired ability to update internal models and minimize prediction errors, leading to a feedback loop where negative emotional responses are amplified and sustained (Goekoop, 2023). Additionally, rumination and ineffective coping strategies may mediate the link between stress and affective disorders (Michl et al., 2013; Zimmer-Gembeck and Skinner, 2016), suggesting avenues for (cognitive behavioral) psychotherapy. Secondly, event-related stress was also linked to missing company in the current affective disorder group, but not in controls. Specifically, having had experienced something unpleasant tended to precede reports of missing company. This finding coincides with other literature reporting the significant role of social support in affective disorders, as well as its potential buffering effect on negative events, indicating a particular need for support in this group after having had experienced something unpleasant (Paykel, 2001; Van den Brink et al., 2018; Zdun-Ryżewska et al., 2018). Thirdly, our findings confirm the directionality of daily affective responses, highlighting DTW's potential to infer causality. For studies examining bidirectional effects, DTW could provide useful.

Future research could further leverage DTW for personalized analyses, developing networks at the individual level to support tailored interventions (Hekler et al., 2019). This approach aligns with calls for dynamic, real-life diagnostics over static, retrospective questionnaires (Roefs et al., 2022; Scheffer et al., 2024). Such individualized EMA-networks could provide valuable insights into the dynamic unfolding of symptoms over time (see Fisher et al., 2017 for an idiographic network-based analysis of EMA-data). These personalized networks might serve as a foundation for targeted therapy and enhance our ability to understand, diagnose, treat, and potentially prevent affective disorders by identifying perturbations in the symptom network early on. Additionally, extending the DTW analysis to include a larger temporal window—looking further into the past or future—could help identify delayed or prolonged directed effects, shedding light on e.g., rumination patterns. To do so, time windows of two or larger could be used instead of one. This broader approach may provide a deeper understanding of how daily events influence emotional states over time, enhancing the prediction of stress responses and recovery. Lastly, it would be valuable to investigate the influence of certain moderators on the relationship between daily events and affect fluctuations, such as resilience factors, lifetime exposure to stressors, and (childhood) trauma.

While strengths have already been described, several limitations also exist, such as the lack of further stratification between groups, as the control group included both 'never-affected' and remitted individuals, and effects in the current affective disorder group were not linked to specific disorders. Additional differences in networks might become apparent if such clustering were added. However, differentiation of the current sample would have resulted in subgroups too small to analyze and could therefore not be executed here. Furthermore, we did not examine potential moderating factors, such as neuroticism, dysfunctional attitudes, or avoidance, that may influence the observed relationships. In addition, negative affect scores were generally low, limiting inferences about high negative affect within the network. However, as real-life longitudinal data was used, these scores are expected to accurately represent the population under study. Moreover, we did not include a direct comparison between DTW and more conventional network analysis methods. Such a comparison could further justify DTW's advantages in the context of daily life stress and mood fluctuations. For interested readers, we refer to recent work by van der Does et al. (2025), which contrasts DTW with VAR-based models in psychological network analysis. Finally, apart from centrality measures, no formal significance testing was conducted to compare effect strengths between groups.

To conclude, this study shows how DTW can be valuable in understanding the (temporal) relationship between stressors, positive events and affect. This relationship seems to differ based on the presence of psychopathology, as affect appeared to be more heavily influenced by daily life events within the current affective disorder group, which further supports dysregulated stress reactivity in those with an affective disorder compared to those without. These findings emphasize the critical role of contextual factors, as neglecting these elements would be to risk overlooking vital information about what influences emotional states. DTW shows particular promise for analyzing EMA-data, offering advantages over traditional methods. We present DTW as a promising starting point for future analyses on daily life psychiatric data, paving the way for more nuanced epistemic investigations and informing both treatment and preventative strategies.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2025.119833.

CRediT authorship contribution statement

Jasmin Pasteuning: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Caroline Broeder:** Writing – review & editing, Conceptualization. **Milou Sep:** Writing – review & editing, Supervision, Conceptualization. **Bernet Elzinga:** Writing – review & editing, Conceptualization. **Brenda Penninx:** Writing – review & editing, Funding acquisition. **Christiaan Vinkers:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Erik Giltay:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

Funding

This work was supported by ZonMw (grant number 09150171910042). The infrastructure for the NESDA study (http://www.nesda.nl) is funded through the Geestkracht program of the Netherlands Organisation for Health Research and Development (ZonMw, grant number 10-000-1002) and financial contributions by participating universities and mental health care organizations (VU University Medical Center, GGZ inGeest, Leiden University Medical Center, Leiden University, GGZ Rivierduinen, University Medical Center Groningen, University of Groningen, Lentis, GGZ Friesland, GGZ Drenthe, Rob Giel Onderzoekscentrum).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

BWJHP is supported by the research project 'Stress in Action' (www.

stress-in-action.nl) which is financially supported by the Dutch Research Council and the Dutch Ministry of Education, Culture and Science (NWO gravitation grant number 024.005.010).

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