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Symptoms of a feather flock together? An exploratory secondary dynamic time warp analysis of 11 single case time series of suicidal ideation and related symptoms

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A R T I C L E I N F O

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A B S T R A C T

Suicidal ideation fluctuates over time, as does its related risk factors. Little is known about the difference or similarities of the temporal patterns. The current exploratory secondary analysis examines which risk symptoms have similar time dynamics using a mathematical algorithm called dynamic time warping (DTW). Ecological momentary assessment data was used of 11 depressed psychiatric outpatients with suicidal ideation who answered three daytime surveys at semi-random sampling points for a period of three to six months. Patients with 45 assessments or more were included. Results revealed significant inter-individual variability in symptom dynamics and clustering, with certain symptoms often clustering due to similar temporal patterns, notably feeling sad, hopelessness, feeling stuck, and worrying.

The directed network analyses shed light on the temporal order, highlighting entrapment and worrying as symptoms strongly related to suicide ideation. Still, all patients also showed unique directed networks. While for some patients changes in entrapment directly preceded change in suicide ideation, the reverse temporal ordering was also found. Relatedly, within some patients, perceived burdensomeness played a pivotal role, whereas in others it was unconnected to other symptoms. The study underscores the individualized nature of symptom dynamics and challenges linear models of progression, advocating for personalized treatment strategies.

1. Introduction

Suicide is a major global concern, with an estimated 703,000 deaths each year worldwide (World Health Organization, 2021). For each suicide, it is estimated that there are 20 times more suicide attempts. Suicidal ideation is even more prevalent, with representative population-based studies estimating the lifetime prevalence to be around 9% (Nock et al., 2008). Research on suicide risk (i.e. suicides, suicide attempts, and thoughts) is primarily conducted within groups employing traditional longitudinal or cross-sectional designs, often relying on linear regression for the analyses (Franklin et al., 2016). From this line of work, we have learned that individuals exhibiting suicidal behavior often present with a history of mental health disorders, and in some cases, previous suicide attempts (De Beurs, Ten Have, Cuijpers, & De Graaf, 2019; Hubers et al., 2018). There are, however, limits to epidemiological studies to understand such highly individual and complex behavior as suicide (Barlow & Nock, 2009; D. P. De Beurs, De Beurs, et al., 2020; Franklin et al., 2016; Millner, Robinaugh, & Nock, 2020). For example, while it is well recognised that female gender is an important risk factor for suicidal attempts, this information has limited

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utility in daily clinical practice, where individual differences and social circumstances more profoundly determine risk for suicide on a case-by-case basis (Hawton, Lascelles, Pitman, Gilbert, & Silverman, 2022; Pompili, 2024). Therefore, clinicians and researchers have turned to novel research designs and analytic tools that are better equipped to allow us to study symptoms at the individual level (DDe Beurs, Cleare, et al., 2020; Kivelä, van der Does, Riese, & Antypa, 2022; Kleiman, Glenn, & Liu, 2023; Kleiman & Nock, 2018) with recent calls to action prioritising such approaches (O'Connor et al., 2023).

Within the field of suicide prevention, the use of advanced technology such as mobile phone apps for data collection is becoming increasingly prevalent. A systematic review of ecological momentary assessment (EMA) studies conducted in 2021 identified 23 studies, with most studies including patients with heightened risk profiles, such as patients recently treated at a hospital for a self-harm episode (Kivelä et al., 2022). These studies generally revealed that both suicidal ideation and common psychological symptoms such as hopelessness exhibit significant fluctuations over brief intervals – ranging from hours to weeks (Kivelä et al., 2022; Kleiman & Nock, 2018). Despite their importance, these studies typically span short periods, often no more than two weeks, with a notable exception being a study that extended up to 42 days (Coppersmith et al., 2023). One of the suggested future directions for research highlighted in the review was to collect data using a longer-term follow up (Kivelä et al., 2022; Nuij et al., 2023). Longer-term EMA studies can help understand if the short-term dynamics also follow a similar long-term trajectory, or if over a longer period, a more stable trend in fluctuations can be found. The Dutch CASPAR (Continuous Assessment for Suicide Prevention and Research) study aimed to test the feasibility of longer-term monitoring of patients with suicidal ideation (Nuij et al., 2018). Within the study, outpatients from Dutch psychiatric departments were invited to monitor several symptoms and suicidal ideation over approximately 3–6 months. The selection of symptoms was partly based on the Integrated Motivational Volitional (IMV) model of suicidal behavior, that states that suicidal ideation and behavior develops through a pre-motivational, motivational and volitional phase (see Fig. 1, O'Connor & Kirtley, 2018). Within the IMV, feelings of entrapment are the key drivers for suicidal ideation. In the CASPAR study, EMA data were collected on four important symptoms within the IMV model: Entrapment, perceived burdensomeness, worrying, and suicidal ideation. Entrapment is argued to arise when one's attempts to escape from defeating or humiliating circumstances are blocked. Within the IMV, it is reasoned that suicidal behavior arises as a reaction to this situation (De Beurs, De Beurs, et al., 2020; O'Connor & Portzky, 2018). Another important theoretical driver is perceived burdensomeness, the perception that significant others would be better off without you (Van Orden, Lynam, Hollar, & Joiner, 2006). Within the IMV, perceived burdensomeness serves as a moderator of entrapment on suicidal ideation, indicating that suicidal ideation is highest when entrapped people additionally have the feeling they are a burden to others. The third variable from the IMV, rumination is defined as repetitive thoughts regarding one's current distress, including the reasons for and the consequences of this distress (Nolen-Hoeksema, 1991). A meta-analysis found a strong positive association between rumination and suicidal ideation (Rogers & Joiner, 2017). A study including a clinical sample found evidence that the relationship between rumination and suicidal ideation could be explained by feelings of entrapment, as stated within the IMV (Teismann & Forkmann, 2017). Within the IMV, the final part of the motivational phase is the transition from entrapment to suicidal ideation. Perceived burdensomeness increases the change of the transition from entrapment to suicidal ideation, as does high levels of rumination (O'Connor & Kirtley, 2018). Additionally, EMA data on four other symptoms were collected: sad mood, feeling happy, feeling hopeless, and feeling content.

Initial analysis of the long term trend of suicidal ideation of five patients that completed 3 assessments a day for a period of 3–6 months found that longer-term trends of suicidal ideation over time can be identified (Nuij et al., 2023). For example, two patients exhibited a steady rise in suicidal ideation, while another experienced a sudden increase following a gradual decline to baseline level. The current study incorporates these data to focus on the dynamics of suicidal ideation and the other symptoms that were assessed multiple times a day within the CASPAR study. To do so, it employs a novel statistical technique called

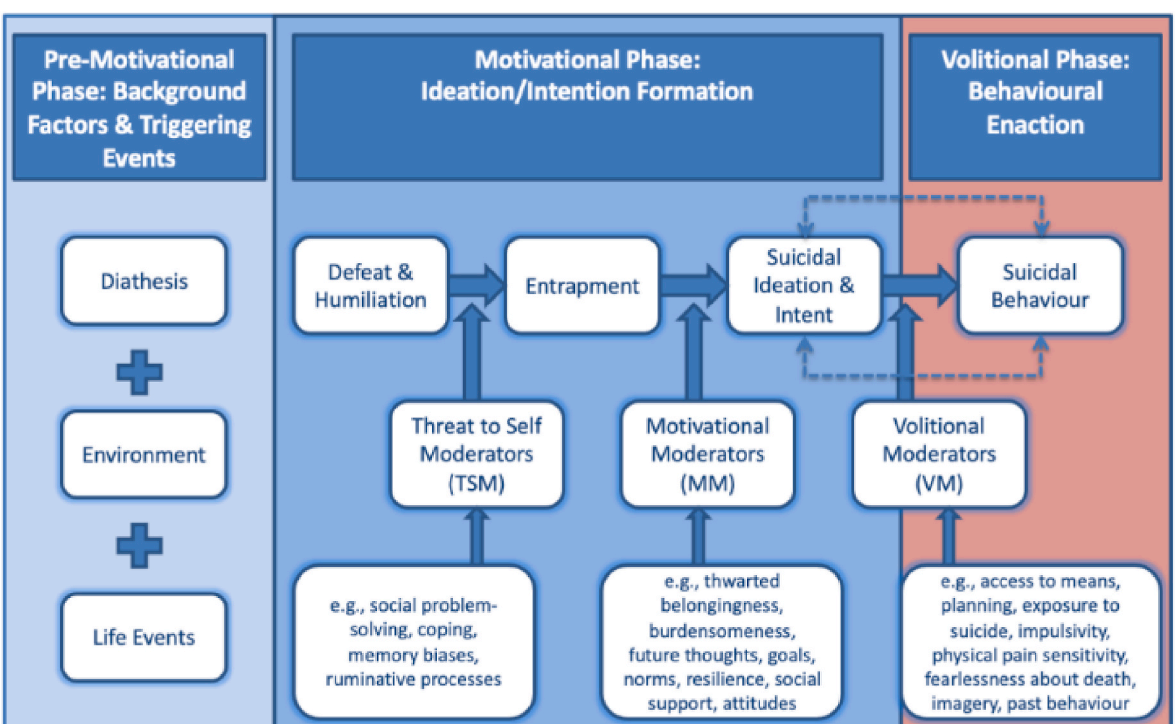

Fig. 1. The integrated motivational volitional model of suicidal behavior (O'Connor & Kirtley, 2018).

dynamic time warping (DTW) which examines the extent to which different risk symptoms have similar time dynamics (Hebbrecht et al., 2020; Koning, Booij, Meijer, Riese, & Giltay, 2023; Mesbah et al., 2023). DTW has been widely used in biomedical research, notably in electro-diagram analysis and speech recognition, but its application within psychiatry or psychology has been limited thus far. To the best of our knowledge, the technique has not been used in suicide prevention research at all.

The few studies that have used DTW have found it to be well suited as a tool to cluster individual symptoms based on the temporal features they share, using either routine outcome monitoring or ecological momentary assessment data (see for example Hebbrecht et al., 2020; van der Does et al., 2023). Traditional time series data analysis often relies on time lag analysis, typically using Vector Autoregression (VAR) methods (Borsboom et al., 2021) which analyses data dynamics within a set time interval, often lag-1. However, this approach can be limiting when assessments occur over varying time spans that do not align with a specific time lag interval, leading to a disconnect in the symptom relationships. It is important to study which timescales, whether they span hours or days, are the most relevant ones for capturing the most crucial dynamics to understand suicidality (Bringmann et al., 2022). DTW may offer a solution to this problem, with more 'elastic' distance measures over various time intervals. This approach enables the study of EMA data that extends beyond just lag-3 relationships, as it also includes lag-0, lag-1, and lag-2 relationships (Booij et al., 2021). DTW analysis also offers insight in the unique dynamic relationship between the symptoms reported by a particular patient. For example, patients might differ in the symptoms that cluster over time with suicidal ideation, offering an important step towards personalized medicine.

Understanding the dynamics over time of theoretical symptoms would also constitute a preliminary step towards a more thorough theoretical understanding of the complex dynamics of suicidal thoughts (De Beurs, De Beurs, et al., 2020; Haslbeck, Oisín, Robinaugh, Waldorp, & Borsboom, 2019; Millner et al., 2020). To this end, the IMV model offers a clear theoretical model that can be tested, but it does not explicitly formalize the proposed inter-relationships between variables. Within psychological science, there is a plea for employing more formalized models in which the relations between each of the separate components are specified (Haslbeck et al., 2019). This approach would enable more precise validation and falsification of any model, and facilitate simulations, allowing researchers to test the effect of potential interventions without burdening patients. By examining the dynamic patterns of suicidal ideation and its risk factors within and across individuals, we can gain a deeper understanding of the suicidal mind. This knowledge can then inform the development of more formalized models of suicidal behavior.

2. Procedure

The data used in this study were collected as part of the CASPAR study between March 2019 and March 2020 (Nuij et al., 2018). CASPAR was a single-group study aimed to test the feasibility of smartphone-based self-monitoring by EMA and a mobile safety plan as components of routine treatment for depressed outpatients at risk of suicide. For the EMA data collection, we relied on the smartphone app mEMA developed by Ilumnivu (illumnivu.com). Every day, between 9:30 a.m. and 6:30 p.m., three daytime surveys were prompted at semi-random sampling points, with a 15-min time window for answering. A total of between 12 and 14 items was assessed at every interval. Patients could use the mEMA app daily for three to 6 months as part of their treatment. The mEMA app monitored suicidal symptoms and provided the patients with insight into these symptoms through a graph, which was then discussed in therapy. Study procedures are described in detail in the protocol paper (Nuij et al., 2018).

3. Patients

Clinicians recruited adult outpatients with suicidal ideation who were treated within three specialized mental health care centres in the Netherlands. Inclusion criteria for patients were (1) being aged $\geq$18, (2) having received a diagnosis of a depressive disorder or dysthymia (as a primary or comorbid disorder), (3) presence of suicidal thoughts, and (4) having access to a smartphone (Android or iOS). Diagnoses and presence suicidal thoughts were determined by the clinician, no additional interviews or assessments were done by the research group. Additionally, patients were excluded if they had insufficient competence in Dutch, had current psychotic symptoms as assessed by their clinician, or were not willing or able to use the smartphone apps. After inclusion, data was collected of Suicidal ideation using items from the Beck Scale for Suicidal ideation (Beck, Kovacs, & Weissman, 1979) and the Self-Injurious Thoughts and Behaviors Interview (Nock, Holmberg, Photos, & Michel, 2007). Other demographic information collected included education, employment status, living situation, comorbid diagnosis and the treating mental health team. For further details on both clinician and patient characteristics, please see the main results paper of the study (Nuij et al., 2022). At the end of the study, 17 patients took part. The current analysis was conducted on data from 11 patients who gathered data of 45 or more assessments over time. This was based on earlier experience with DTW analysis. There were 6 participants who were excluded, as they each had between 2 and 25 measurements with complete data, with an average of 11.3 measurements and a standard deviation of 8.3. Due to the inability to create stable (directed) networks with such a limited number of measurements, these 6 participants were excluded from the study.

4. Items

Four key symptoms from the IMV model were included in the analysis: Entrapment, perceived burdensomeness, worrying and suicidal ideation. We also gathered data on 4 other symptoms: sad mood, feeling happy, feeling hopeless and feeling content. A single item per symptom was selected from existing questionnaires with established psychometric properties. In the current study, the following symptoms where assessed: suicidal ideation (based on the Beck Scale for Suicidal ideation (BSS (Beck, Steer, & Ranieri, 1988)): 'I have the desire to end my life'); entrapment (based on the Entrapment Scale short form (De Beurs, De Beurs, et al., 2020): 'I feel entrapped'); perceived burdensomeness (based on the Interpersonal Needs Questionnaire (INQ (Van Orden, Witte, Gordon, Bender, & Joiner, 2008): 'I'm a burden to others'); restless (based on the Generalised Anxiety Disorder (GAD): 'I feel restless'); worrying (based on the Ruminative Responses Scale (RSS: (Nolen-Hoeksema, 2003): 'I can't escape my thoughts'); depressed mood (based on the Patient Health Questionnaire (PHQ: (Kroenke, Spitzer, & Williams, 2001): 'I feel depressed'); hopeless (based on the Short Defeat and Entrapment Scale (SDES (Griffiths et al., 2015): 'I feel hopeless'); feeling happy (based on the Hospital Anxiety and Depression Scale (HADS: (Mykletun, Stordal, & Dahl, 2001): 'I feel cheerful'); and feeling content (based on the Patient Health Questionnaire (PHQ): 'I feel satisfied'). All items used in the current study were rated on a 7-point Likert-type scale with the answer options ranging from 1 (completely disagree) to 7 (completely disagree), with a neutral option 4 (not disagree nor agree). Patients were instructed to rate the items 'at this moment'.

5. Statistical analysis

A range of different analyses were conducted to focus on the individual dynamics of suicidal ideation and related symptoms using a clustering algorithm based on dynamic time warp (DTW). First, we plotted the standardized item scores over time using colour coding, to get a sense of the changes in scores per item within each of the patients.

Second, undirected DTW analyses were presented, in which the distance between each pair of the standardized items was assessed, yielding a low value when these followed a similar trajectory over time. In the undirected DTW symptom networks items connected by edges covaried strongly in time. Third, directed DTW symptom networks were estimated with 3 different time lags (lag-1, lag-3, and lag-5) to study the order in time of changes in item scores. This approach tests whether changes in item scores preceded or followed that of similar changes in other symptoms within a particular patient.

We reverse coded the items “I feel cheerful’” and “I feel satisfied”, to maintain consistency in the measurement scale across all items, after which all items’ scores were group-level standardized. This reverse coding was implemented so that the entire item scale uniformly ranged from low complaints to high severity of complaints. This ensured that all items were evaluated on a similar scale of severity, with green edges in the network designated to represent the expected relationships between symptoms, and red edges indicating more unexpected and counterintuitive relationships.

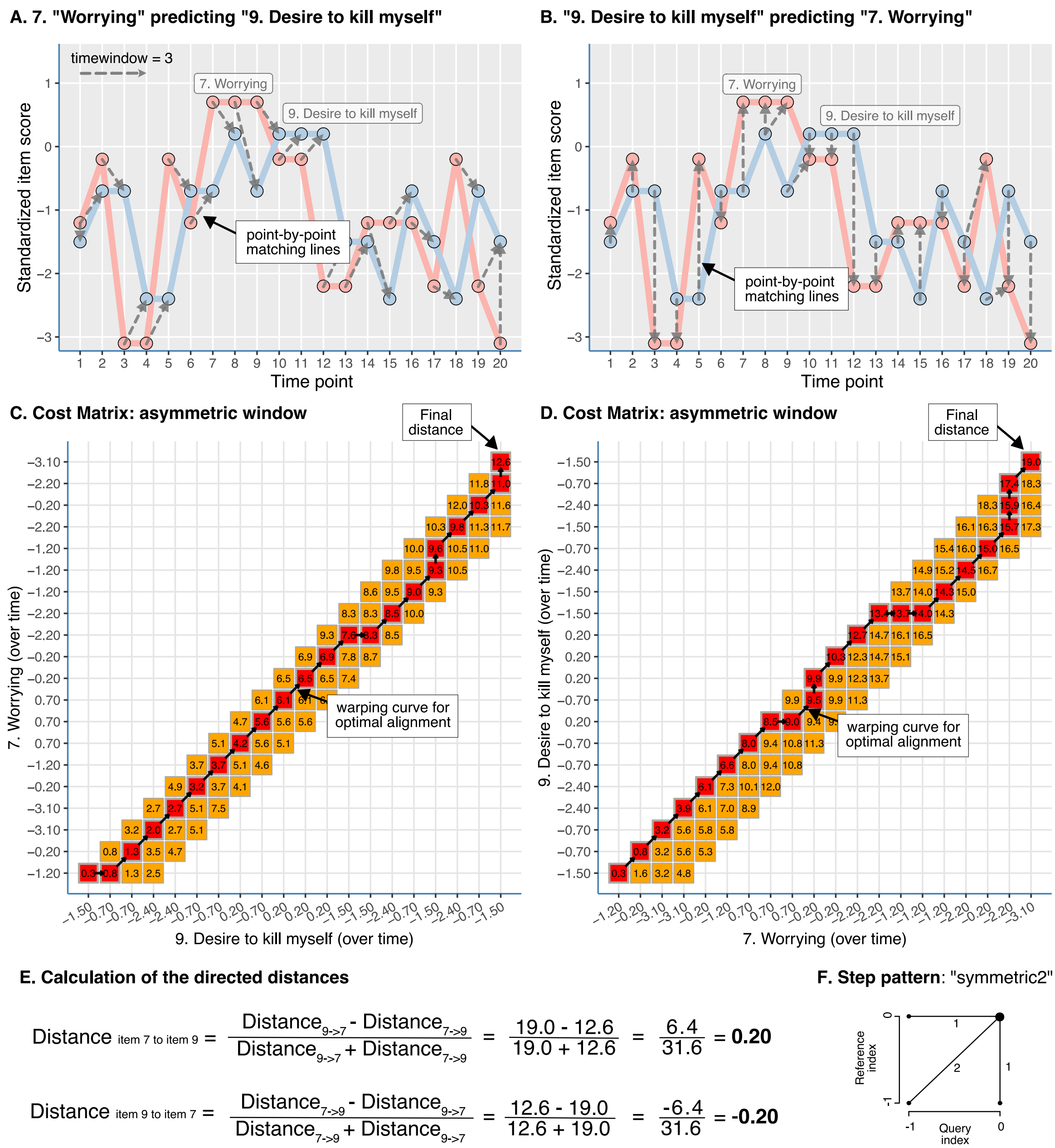

Fig. 2. A visualization of the directed Dynamic Time Warping (DTW) analysis, applied to track the variations in two item scores over time in a single participant. Panels A and B represent the fluctuating scores of the two items across a 20 time points. Black dotted arrows illustrate the process of warping one item’s trajectory to align optimally with another forward in time, adhering to the constraint of an asymmetric time window. This constraint limits the alignment adjustment to within up to three timepoint after the current assessment. Panels C and D show the Local Cost Matrices (LCMs). The DTW algorithm constructs an LCM by finding the path that minimizes the discrepancy between pairs of item scores. This process begins at the matrix’s lower left corner (LCM [1, 1]) and progresses iteratively to its upper right corner (LCM [20, 20]). The algorithm selects the path with the least increase in cost at each step, guided by an asymmetric window of size three and a “symmetric2” step pattern. The “final distance” for each path (i.e., 12.6 and 19.0) reflects the total accumulated cost of this optimal warping. Panel E: This panel show the directed DTW distance calculations for the pair of item scores. The resulted final distances are 12.6 and 19.0, respectively for the direction from item 7 to item 9, and for the reverse direction. Next, the statistic ‘directed distance’ was calculated using the formula presented in Panel E. This resulted in a positive value of 0.20 for the distance from “7. Worrying” to “9. Desire to kill myself”, and a negative value for the opposite direction, which indicated that changes in worrying preceded suicidality.

We calculated the variance within each participant for each item, and then computed the average. This average is plotted in a figure, with the error bars representing the standard error of the variance among the 11 participants.

6. Undirected DTW

Undirected DTW analysis involved calculating the distance between each symptom pair, as detailed in previous literature (Hebbrecht et al., 2020; Koning et al., 2023; Mesbah et al., 2023). Undirected DTW effectively aligns these two series by 'stretching' or 'compressing' them in time. This flexibility allows DTW to compare the patterns of symptom

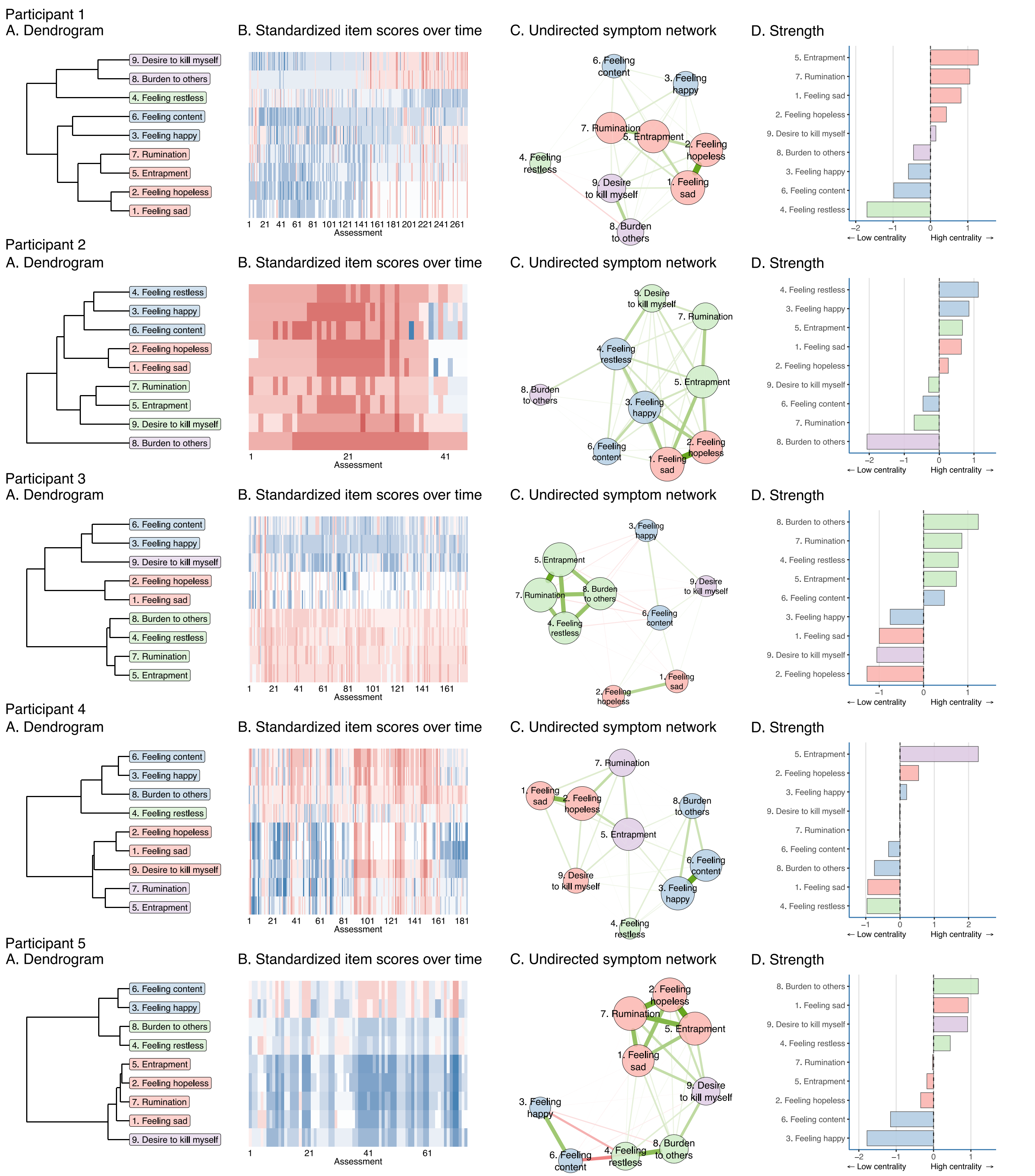

Fig. 3. Individual undirected networks of patients 1 to 11. Panel A: Dendrograms, Panel B: Standardized item scores over time. Panel C: Undirected symptom network Panel D: Strength of nodes within network. Colouring indicates clustering according to the DTW analysis.

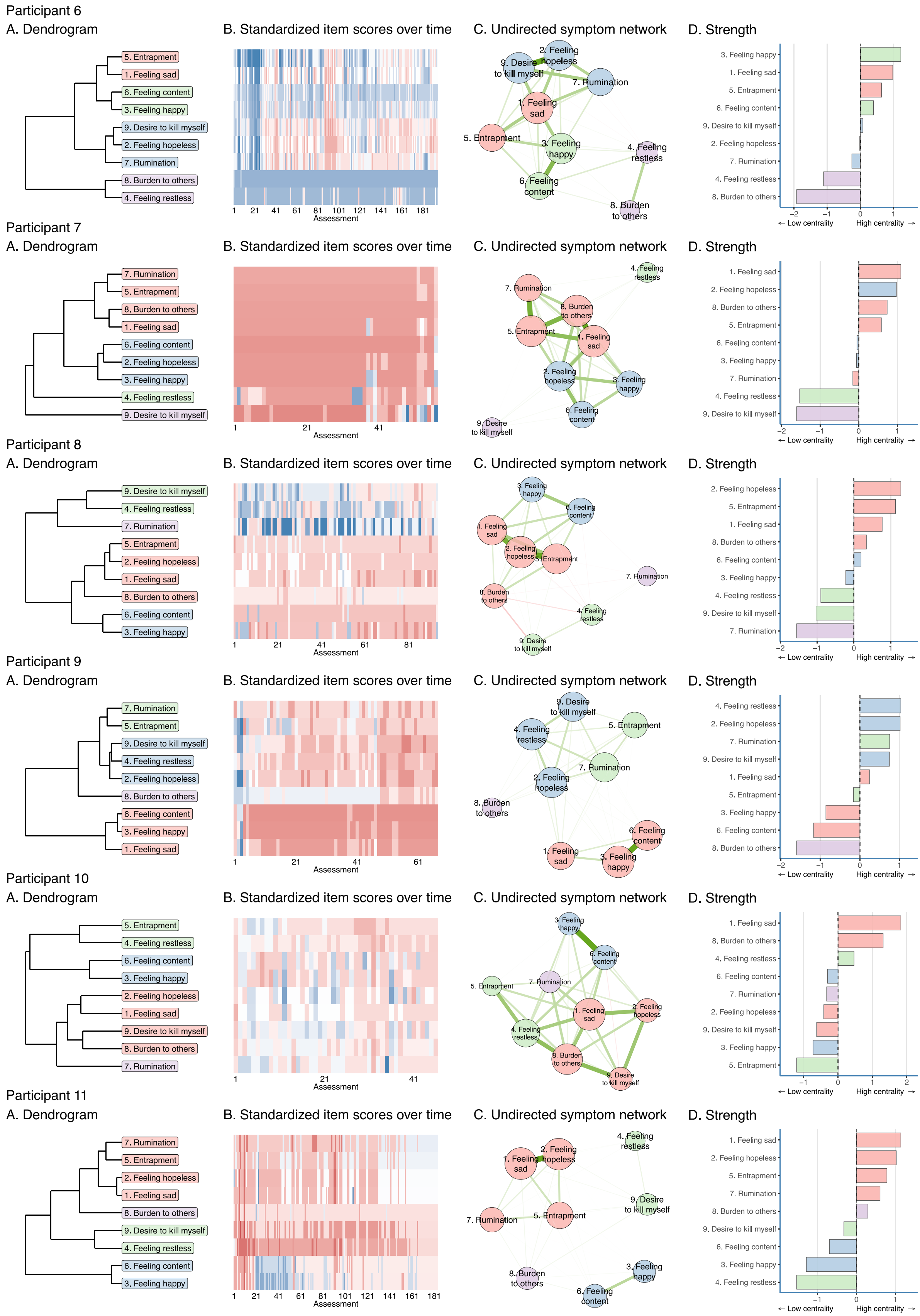

Fig. 3. (*continued*).

changes over time, even if these changes do not occur simultaneously. We employed a Sakoe-Chiba bandwidth of 1, which restricts the alignment to only consider points that are close in time, specifically within a range of one time point either before or after a given point. A 'symmetric2' step pattern was used, that ensures that each point in one time series is matched with one or more points in the other time series without favouring either time series. Distances were 'normalized' according to the number of assessments within that individual. This yielded a distance matrix for each participant. The distance matrices were symmetric, so that the distance from symptom 1 to symptom 2 is identical to that from symptom 2 to symptom 1. A small distance indicates that the two symptom scores covary strongly in time.

A dendrogram (Panels A, Fig. 3) was then created that shows which variables share the largest similarity in dynamics over time. It is based on the Ward's (D2, i.e., general agglomerative hierarchical clustering procedure) clustering criterion on each individual distance matrix. Next, the individual item scores were plotted over time and color-coded for severity (Panels B, Fig. 3). Third, the undirected symptom networks (Panels C, Fig. 3) were created that illustrate the dynamic connections, with the thickness of the lines indicating the similarity of the trajectories in time. Finally, standardized centrality of each of the symptoms was calculated and plotted as bar graphs (Panels D, Fig. 3).

Furthermore, the analysis of the 11 distance matrices were extended to the group level, resulting in three distinct visual representations: a dendrogram, a network plot, and a bar graph of standardized centrality strengths of each symptom within the network. In the network visualization, significant connections are marked with asterisks. These indicate edges that demonstrate a significantly smaller distance ($p < 00.05$) compared to the average of all other distances, after adjustment for the variance of scores of each item over time for each participant.

7. Directed DTW

For each of the 11 patients, we also computed a directed DTW distance matrix (Koning et al., 2023; Mesbah et al., 2023). This analysis technique enabled us to discern the temporal patterns among various symptoms. This is particularly effective in determining how one symptom change might precede similar changes in other symptoms, thus revealing the directional dynamics of symptomatology over the course of time. Our implementation of directed DTW utilized an asymmetric time window, to constrain the dynamic alignment in a forward temporal direction. We employed an asymmetric variation of the Sakoe-Chiba band to measure similarities between temporal sequences, accommodating for differences in the timing of symptom changes during therapy. This indicates whether fluctuations in one symptom (A) at a given time (t-1) can reliably predict changes in another symptom (B) at a subsequent time (t). This bidirectional analysis (A predicting B and vice versa B predicting A) is instrumental in establishing predictive relationships between symptoms, moving us closer to identifying Granger causative links (Granger, 1969).

Fig. 2 explains the calculation process for the directed DTW distance in more detail. As the measured directed distance from item 7 to item 9 is positive, it implies that variations in item 7 precede changes in item 9. This relationship positions item 7 as a predictor for item 9. The directed distance values range from −1 to 1, where the magnitude of the distance reflects the strength of the temporal relationship between the items. A directed distance of 1 would suggest that the values of item 7 would be perfectly matched with values of item 9 at a subsequent time point. Conversely, when two items exhibit identical trajectories over time, their directed distance is zero, indicating no predictive relationship.

The directed network plots visually represent the directed distances among symptoms, with symptoms depicted as nodes. The time lag methodology was hierarchically structured to include lower lags within higher ones. For instance, lag-3 encompassed Lag-0, Lag-1, and Lag-2. Additionally, within a time-window of 3, we evaluated the in- and out strengths of each symptom. A symptom with high out-strength centrality often precedes changes in various other symptoms, as indicated by multiple arrows starting from it. In contrast, a symptom with high in-strength centrality is typically following changes in several other symptoms, evident from numerous arrows pointing towards it.

Next, we assessed group-level effects among the 11 patients. The directed distance matrices were statistically analysed to assess significant deviations from zero, using t-tests. In our directed network plots, the arrow with the asterisk depicts when the directed distance was significantly greater than zero at the group level ($p < 0.05$).

Our analysis emphasizes item 9, "desire to kill myself," as a pivotal node. To understand the interaction of this symptom with others, we computed the combined in- and out-strength for each node in relation to this central one. This approach helped identify which symptoms typically preceded changes in suicidal thoughts and which ones followed them. We also aggregated these matrices to calculate the standardized in- and out-strength centrality, using mixed models with a participant-specific random intercepts.

The "dtw" (version 1.23–1), "lme4" (version 1.1–34), and "qgraph" (version 1.9.5) packages for the R statistical software were used (v4.2.2; R Core Team, 2020).

8. Results

The sample consisted of 6 women and 5 males with a mean age of 34.6 years (range = 20–50, $SD = 9.9$). Patients answered on average 129 surveys (range = 45–282 surveys, $SD = 79.8$). On average, patients were engaged with EMA data collection for 96 days (range = 49–193 days, SD = 41.5 days).

Ten patients had a diagnosis of MDD and one patient of dysthymia. All patients reported suicidal ideation at the start of the study. Ten patients had made a suicide plan at least once in their lives, and seven patients had done a previous suicide attempt.

8.1. Standardized symptom scores over time

Panel B of Fig. 3 displays the severity of symptoms using a colour-coded scale, where red represents higher severity and blue represents lower severity. This visualization aligns with the dendrograms in Panel A, arranging symptoms so that similar trajectories are positioned next to each other for easier comparison and analysis. As can be seen in panel B of Fig. 3, all patients showed different patterns of symptom severity of symptoms.

For example, panel B of Patient 1 mainly shows a blue color, reflecting lower overall symptom severity. Panel B of Patient 2, however, is predominantly red, denoting high severity across all symptoms during the entire study period. Both within and between patients, the graphs reveal high variability of symptom severity. For instance, Patient 6 demonstrates that the symptom "burden to others" showed little variance over the entire study period, whereas the symptom "desire to kill myself" fluctuated more heavily. Although most patients displayed variability in scores over time, Patient 7 seemed to continuously report consistently high scores on most symptoms, indicating the long-term stable presence of many symptoms. Fig. 4 below illustrates the mean variance of all symptoms for the 11 patients. As can be seen, "burden to others" had the lowest variance, followed by "feeling stuck", although confidence intervals overlapped and were very wide due to the small sample size.

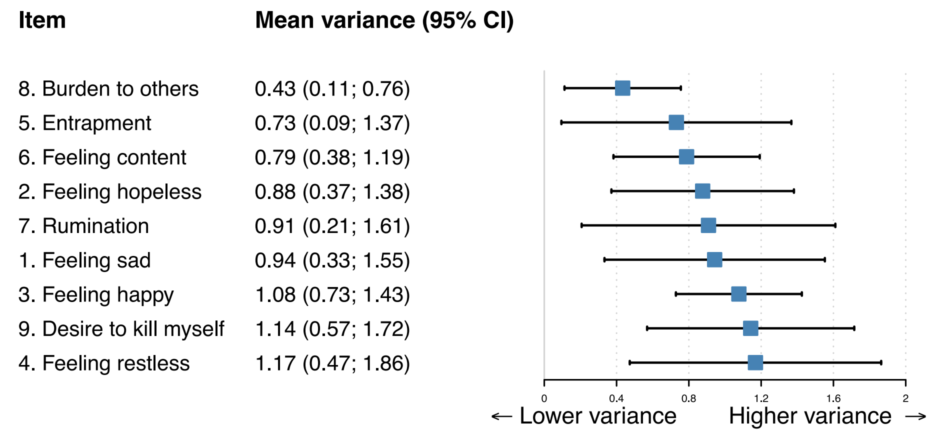

Fig. 4. The mean variance of symptoms.

8.2. Clustering over time

Panels A of Fig. 3 display the individual patient dendrograms. Four symptoms (feeling sad, hopelessness, feeling stuck and worrying) often co-occurred within individuals, but in different combinations. For example, for all but three patients the symptoms "feeling sad" and "feeling hopelessness" clustered together, and "feeling stuck" clustered with "worrying" for all but two patients. However, within two patients (Patients 8 and 10) worrying did not seem to cluster with any other symptoms. This pattern, that a symptom clustered with other symptoms in some patients but did not cluster with other symptoms in other patients, was found more often. For example, the symptom "burden to others" did not cluster with any other symptom in three patients (Patients 2, 8, and 11) whereas in three others it was actually the most central symptom in the network (Patients 3, 5, and 7). Similarly, the symptom "desire to kill myself" was not related to any symptom in 3 patients (for patients 2, 7, and 11), but clustered with three other symptoms in patient 3. Two core symptoms in the IMV model, "feeling stuck" and "burden to others", clustered together in patients 3 and 8, but not in others. These findings highlight the variability in symptom clustering and centrality among individuals, and they warrant special attention for clinicians to help to make sense of the suicidal process for each patient.

Fig. 5, Panel A displays the dendrogram that revealed at the group level which symptoms over time show similar trajectories, and thus clustered together.

The symptoms hopelessness, worrying, entrapment, feeling sad and suicidal ideation were grouped in one cluster of 5 symptoms, which we labelled as "reinforcing negative mood symptoms". "Burden to others", a motivational factor, clustered with "feeling restless", a volitional factor. Finally, "feeling happy" clustered with "feeling content".

8.3. Undirected networks

All individuals had unique networks, although some similar patterns were found (Fig. 3, panel C). The symptoms we labelled reinforcing negative mood symptoms (worrying, feeling stuck, feeling hopelessness, feeling sad and desire to kill myself) indeed often clustered together, with many different combinations across individuals. For example, in patient one, two and four, "worrying", "feeling hopeless", "feeling stuck" and "feeling sad" were strongly connected to each other and to "desire to kill myself". In other patients, such as patient 6, "burden to others", "feeling content" and "feeling happy" where also closely tied to the other symptoms.

Patient three stood out, with a cluster of the symptoms "burden to others", "worrying", "feeling stuck" and "feeling restless" that did not connect with other variables in the network. At the group level, the five reinforcing negative mood symptoms were found to cluster together and occupied the most central position within the network (Fig. 3, panel C), with "desire to kill oneself" being least central of the five. "Feeling a burden" and "feeling restless" were connected to one another, but not to other variables in the network, ranking them also among the least central nodes. This illustrates that although overall patterns can be deducted, each individual has a unique network.

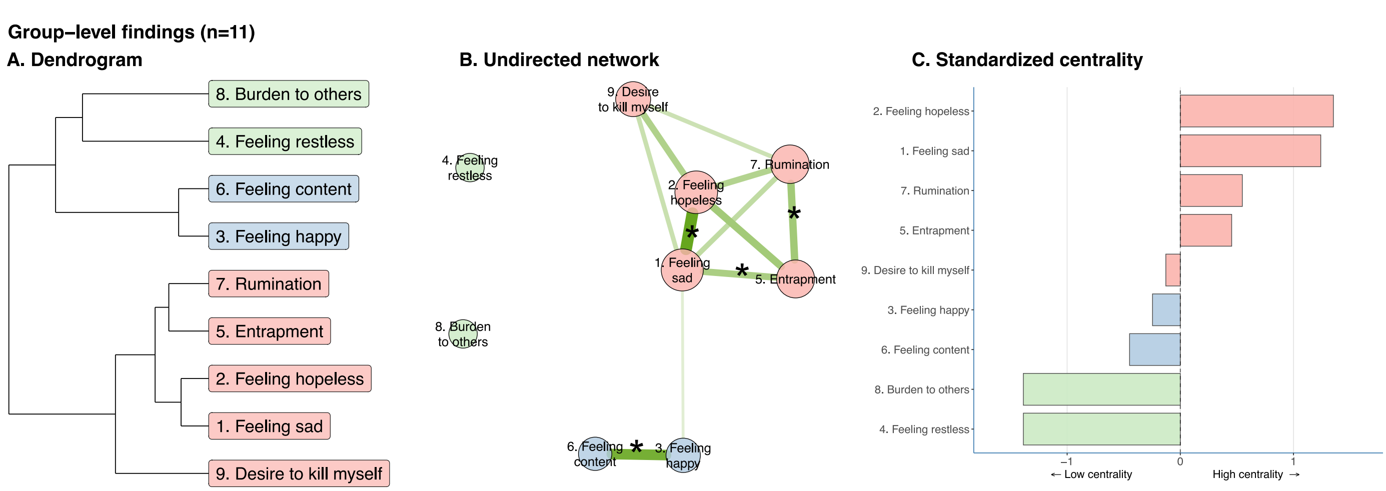

Fig. 5. Undirected group-level findings. Panel A: dendograms, Panel B: undirected symptom network Panel C: Strength of nodes within network. Colouring indicates clustering according to the DTW analysis.

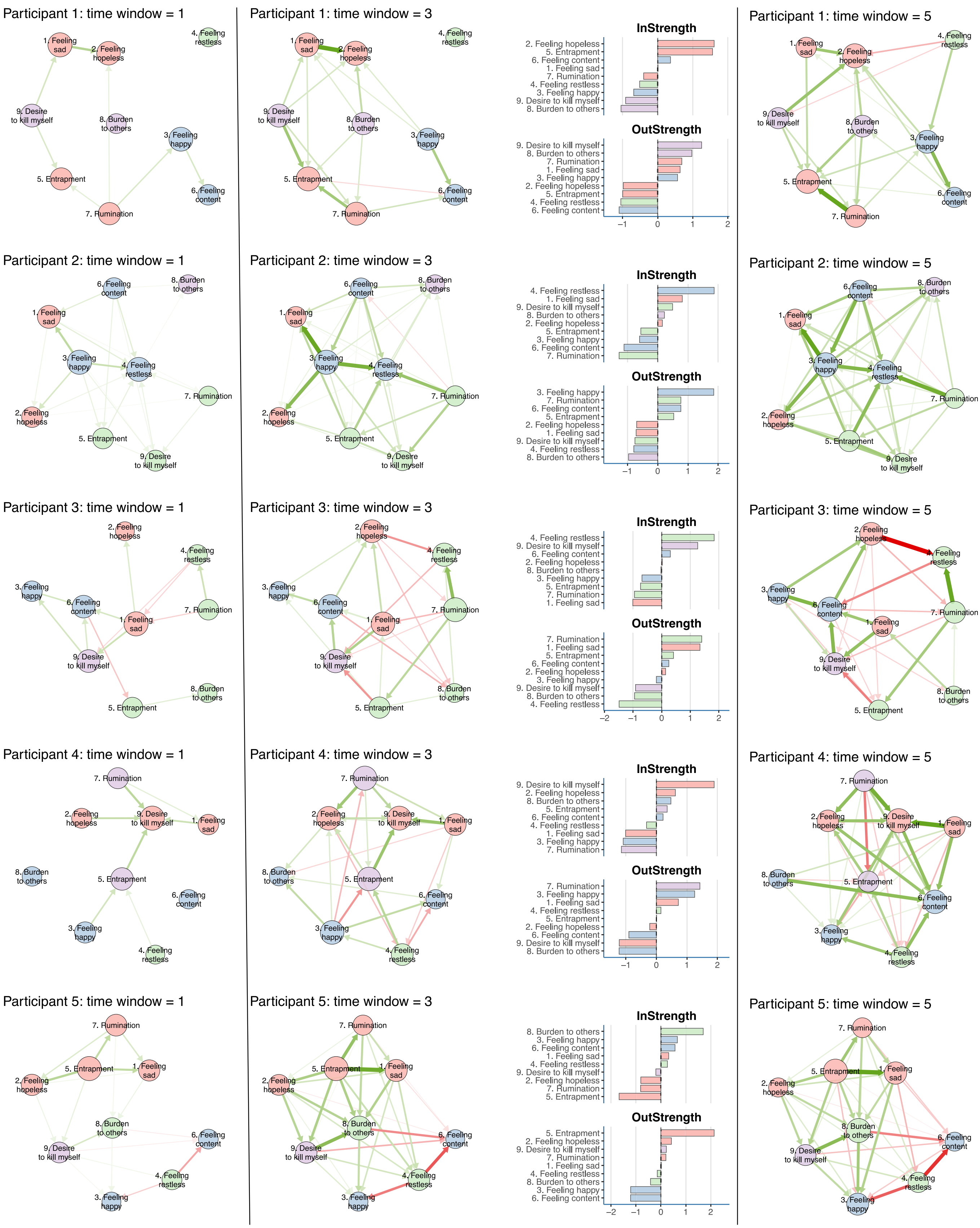

Fig. 6. Individual directed networks. Panel 1: Time window lag 1. Panel 2: Time window lag 3 with centrality measures. Panel 3: Time window lag 5. Colouring indicates clustering according to the DTW analysis.

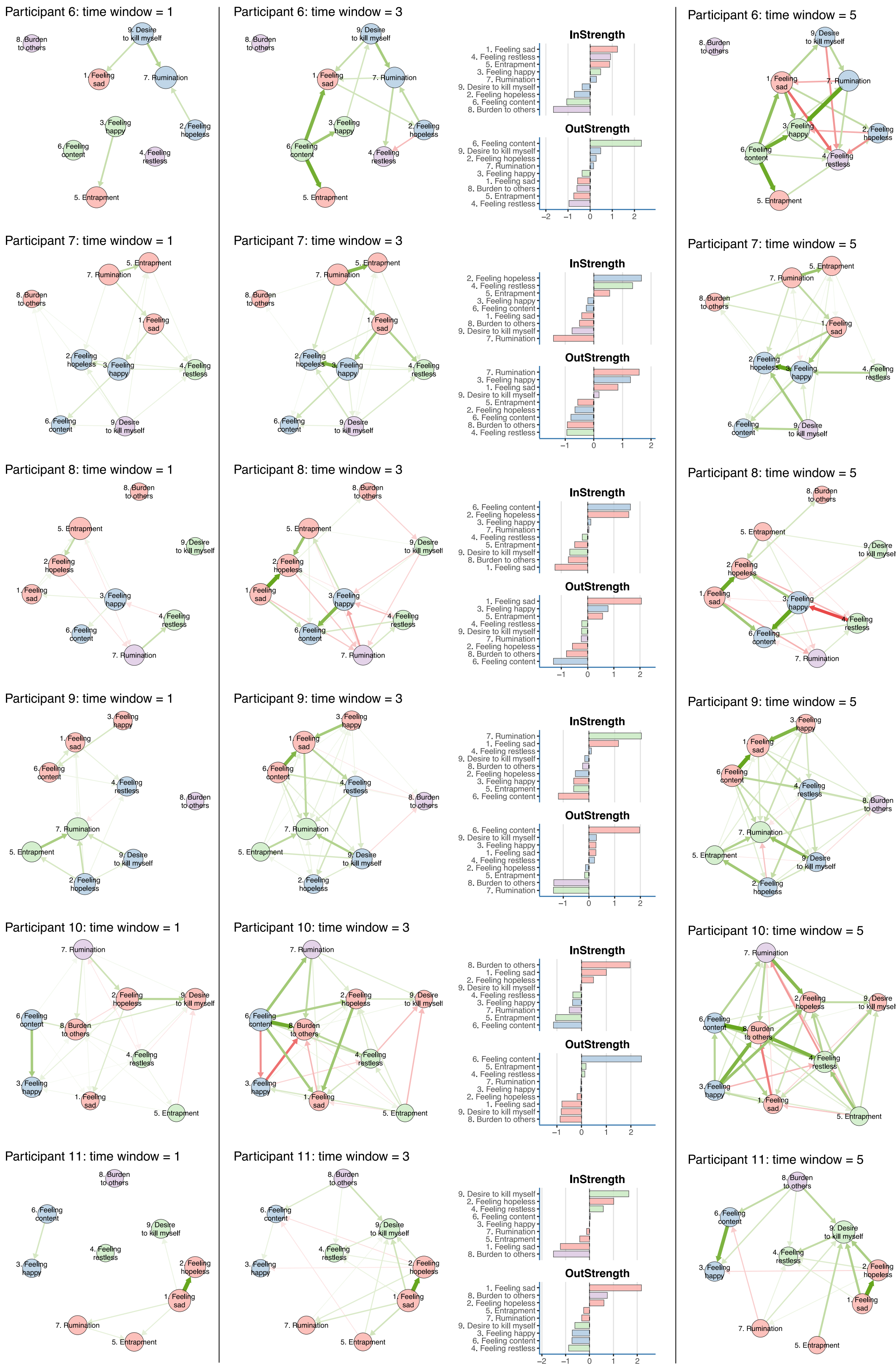

Fig. 6. (*continued*).

8.4. Directed networks

At the individual level, Fig. 6 present the networks for three different time windows for all 11 individuals.

The first network (time-window = 1) explores the relationship between the previous assessment and the next (i.e., lag-1), the second network (time-window = 3) looks at all time-lag associations between one and three times points later (i.e., lag-1 through lag-3), while the third network (time-window = 5) looks at all time-lag associations between one and five times points later (i.e., lag-1 through lag-5). A pattern emerged from these analyses: the longer the time interval, the more edges that appeared in the networks. Similar to the undirected networks, the reinforcing negative mood symptoms seemed to influence each directly over time, although the direction of this influence varied among individuals. For example, for Patient 1, “desire to kill oneself” seemed to directly influence “feeling stuck”, whereas for Patient 9 the direction is opposite. “Worrying” and “feeling stuck” consistently occupy roles with high in- or out-strength in most directed networks, either as driver of other symptoms, for instance in Patient 5, or as a symptom influenced by others, such as in Patient 9. The role of perceived burdensomeness also seems to differ between patients. For example, in Patient 6, “burden to others” was not related to the other symptoms within the network. However, when zooming in on Patient 1, “burden to others” seemed to be central, mainly driving other variables. Some connections in red were counterintuitive. For example, in Patient 4, it seems that a higher level or worrying at one time point predicts a lower level of entrapment at the next (or vice versa a lower level of worrying preceding a higher level of entrapment).

Fig. 7 presents directed time-lag networks at the group level.

Over time, “feeling sad” and “desire to kill myself” were not connected to the other variables. Interestingly, the sense of being a burden to others seemed to be mainly driven by other symptoms, such as feeling stuck. When looking at the centrality indices, it does seem that the reinforcing negative mood symptoms indeed have a direct effect on suicidal ideation, and over time perceived burdensomeness seems to be influenced by suicidal ideation instead of the other way around. Yet, these findings need to be interpreted cautiously, as they did not demonstrate statistical significance within the limited sample size of 11 patients.

9. Discussion

In this paper, we investigated the time dynamics of psychological symptoms for suicidal ideation using ecological momentary data from 11 psychiatric patients. More specifically, we applied a technique called DTW that allowed us to investigate the temporal clustering of symptoms over time. Although our findings are limited because of the small number of patients (but a large number of assessments per patient), the uniqueness of the data (i.e. EMA collected over a period of at least 1.5 months) and the focus on clustering of dynamics over time resulted in findings that could provide useful for further studies. Below, we organized the results according to each psychological symptom for readability and clarity.

9.1. Entrapment

The IMV model identifies entrapment as the most central driver of suicidal ideation (O’Connor & Kirtley, 2018). Indeed, different studies pointed to the role of entrapment in suicide risk in both cross-sectional and prospective research studies (O’Connor & Portzky, 2018). In our analyses of both the individual and the group cross-sectional networks, entrapment played a central role, often co-varying with other symptoms within the network. Specifically, entrapment, worrying and feeling sad were found to follow similar trajectories over time in most patients. At the group level, these three symptoms also clustered with suicidal ideation and hopelessness resulting in a cluster of 5 symptoms that we labelled “reinforcing negative mood symptoms”. These findings support the hypothesis that depression may function as an evolutionary response to situations (or feelings) of entrapment (Gilbert & Allan, 1998). Consistent with this conceptualisation, the state of entrapment gives rise to a desire to move and escape from a painful situation or thoughts, and when that is hindered one is more likely to feel hopeless, depressed, and suicidal.

From a network theory perspective, our finding that these feelings of entrapment, mood, hopelessness, rumination and suicidality have similar dynamics over time tells us something about potential causal mechanisms (De Beurs, De Beurs, et al., 2020). These psychological symptoms seem to interact either contemporaneously or over a very short period of time, and negatively influence each other over time. When (at least) one of the symptoms is activated by, for example. An external stressor such as a lay-off, the activated symptom is likely to activate the other symptoms. Then, the symptoms can get into a positive feedback loop, resulting in ongoing increases of symptom severity that can persist even in the absence of the initial stressor (Borsboom, 2017). Additionally, this is consistent with the kindling hypothesis (Post, 1992) which posits that lower levels of stress are required to re-activate the symptoms and the feedback loops.

When looking at the directed group network, entrapment was found

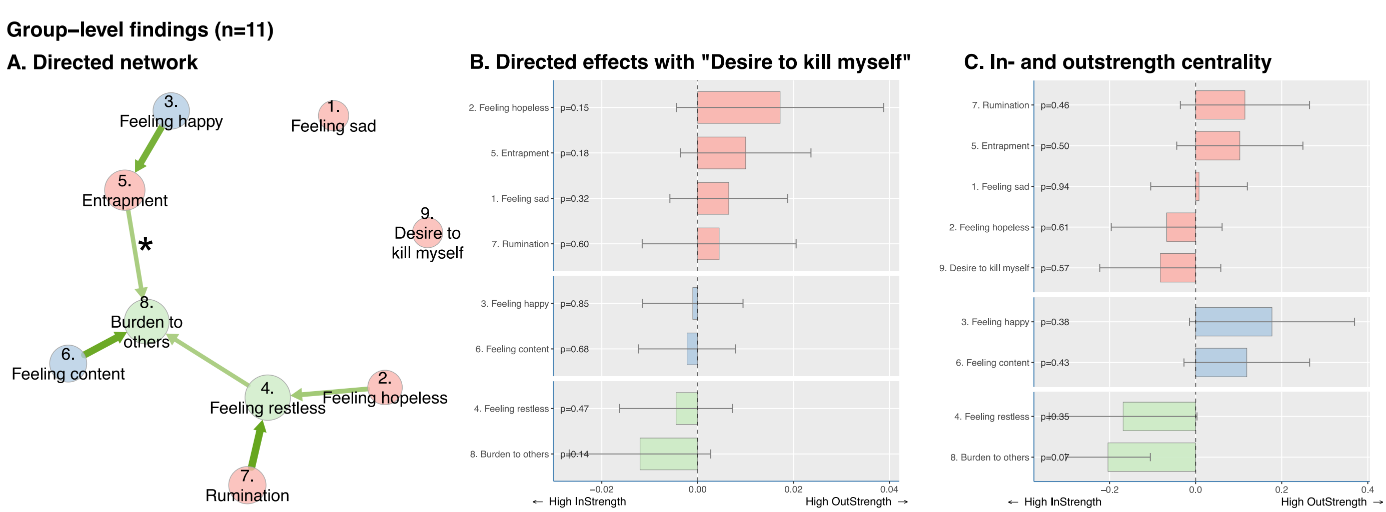

Fig. 7. Group level directed networks. Panel A: Directed network B: Directed effects with “desire to kill myself”. Panel C: In and outstrength centrality. The asterix in Panel A denotes a significant arrow on the group level.

to have high out-strength. This suggests that it was a main driver of other symptoms, including suicidal ideation. This is in line with the central assumption of the IMV model, that clearly positions entrapment as a central and proximal risk factor for suicidal ideation. This suggests that targeting entrapment in treatment in these patients could have a beneficial effect on most symptoms of suicidality and suicidal ideation itself. However, it is of importance to take individual differences into account. Where in several patients entrapment was indeed a likely driver of other symptoms, in some patients, it seems that other factors were driving entrapment. Assessing symptoms networks within individuals could lead to more nuanced and effective personalized treatment strategies for those at risk of suicide (Hebbrecht et al., 2020; Wright & Woods, 2020).

9.2. Perceived burdensomeness

Many studies found that perceived burdensomeness has a direct effect on suicidality above and beyond entrapment (de Beurs et al., 2018; Forkmann & Teismann, 2017). In the current study, in contrast to entrapment, perceived burdensomeness showed large variability in the centrality; it was more often one of the least central nodes within the networks, but the most central in others. When looking at the standardized symptoms scores, perceived burdensomeness showed little variance per participant over the study period. This result differs from earlier EMA findings that reported large fluctuations of perceived burdensomeness over time within a timeframe of several days (Kleiman et al., 2017). However, a later EMA study did find perceived burdensomeness to be relatively stable over time, with mainly fluctuations around their individual average (Rogers & Joiner, 2019). In the overall network, perceived burdensomeness, which in the IMV is a motivational factor, clustered over time with feeling restless, a volitional factor. Indeed, feeling restless also showed low variation over time, but if variation occurred, it followed a similar pattern to that of perceived burdensomeness. The co-occurrence of a motivational factor and a volitional factor might suggest that perceived burdensomeness not only affects suicidal ideation, as found in many studies, but also potential volitional factors. Better understanding of the relationship between motivational and volitional factors might help to better appreciate the temporality and cyclical nature of suicide risk within the IMV model. As with entrapment, it is important to take individual differences into account.

9.3. Suicidal ideation

As the individual directed and undirected networks showed, suicidal ideation is highly individual. For some patients, entrapment seems to drive suicidal ideation, but the reversed relationship was also found. For others, perceived burdensomeness played a central role, as posited by both the IMV model and the interpersonal theory of suicidal behavior (Van Orden et al., 2010). These results highlight the importance of nuance when interpreting the step-wise reasoning of many of predominant explanatory models of suicidal behavior. For example, within the IMV model, psychological symptoms such as entrapment precede suicidal ideation, and suicidal ideation is not hypothesized to have an effect on entrapment or any of the preceding symptoms such as worrying. This step-wise reasoning helped both researchers and clinicians to understand the development of suicidal ideation as a longer process of interacting symptoms, and stimulated thinking about the transition from thoughts to action as a sequential process. Of course, as clinicians, researchers and patients know, in reality the relation between entrapment, suicidal ideation, but also other symptoms such as worrying, depressive feelings and hopelessness is less straightforward (Kleiman et al., 2017) with factors influencing each other over time in feedback loops. Indeed, in the directed networks, suicidal ideation showed either strong instrength or strong outstrength, confirming the central role of suicidal ideation in the temporal networks.

The directed group network suggests that suicidal ideation is mainly driven by entrapment and worrying, and also by feelings of sadness and hopelessness. This is in line with the central tenet of the IMV model, and is backed up by many other studies (O'Connor & Portzky, 2018). It illustrates that suicidal ideation does not occur in a vacuum, but is influenced by feelings of defeat and entrapment, amplified by rumination over these thoughts and feelings. When asking about suicidality, asking about the level of entrapment and worrying could provide important insight into the mind of a patient who is suicidal.

9.4. Limitations and strengths

This study has several limitations, the most important one being the small sample size. Therefore, robust analysis at the group level of clustering of symptom dynamics is likely to be unstable, limiting the generalizability of our findings. An important reason for the small sample size was that patients reported technical problems such as receiving no or too many prompts. Also, due to the COVID pandemic, recruitment period was far shorter than initially anticipated. Another limitation was the time frame. Although 3–6 months is a long time for self-monitoring, the suicidal process might develop over even longer periods of time. As longer monitoring via daily prompts seems not feasibly or preferable, another future option would be to work with unobtrusive data, i.e. data collected using for example social media usage or movement. Despite studies showing that it is feasible to predict mood using unobtrusive collected data via smartphones (Asselbergs et al., 2016), this development is still in its early stages, and as such has not been applied within the field of suicide prevention (Moreno-Muñoz et al., 2020). Although the patients in our study reported suicidal thoughts at the beginning of the study, as far as we can tell, no patient had a serious crisis resulting in a suicide attempt during data collection. Relatedly, given the small sample size among a rather homogeneous group of depressed outpatients, the generalizability of our findings are limited, and future studies should apply DTW to data collected among different patient samples. For example, future studies might focus on patients in a more acute risk period for suicidal behavior to allow us to learn about the changing dynamics at this crucial moment in the suicidal process.

As the weeks after discharge from a hospital are considered a high-risk period for suicidal behavior, one could learn a lot about the actual suicidal process by following these patients. Also, it might prove useful to differentiate between different subgroups of suicidal patients, such as between patients who are chronically suicidal and patients who became suicidal after a recent stressor (de Winter, Meijer, Enterman, et al., 2023; de Winter, Meijer, van den Bos, et al., 2023).

The IMV model contains many more variables when compared to the ones we included in our study. Therefore, our analysis and monitoring are limited to the constructs we assessed. Relatedly, our analysis also only contained information on psychological processes, and not (psycho)social (e.g. critical live events) and behavioral factors (e.g. sleep parameter), or any other relevant (environmental) factors beyond the psychological domain (van der Wal et al., 2021). This is a notable limitation, given their potential significant influence on the progression from suicidal ideation to suicidal behavior. Future studies might apply unobtrusive methods to collect data, allowing to include information on sleep, movement and also social activities (e.g., via digital phenotyping (Jagesar, Vorstman, & Kas, 2021).

Additionally, the usage of one single item rated on a 7-point Likert type scale also limits the reliability and validity of the assessed constructs. Randomly offering different items to assess the same construct might improve validity.

A strength of this study was the application of a flexible technique that offers insight into the cluster over time. DTW has several benefits compared to other analyses techniques that are based on Vector Autoregression (VAR: Bringmann et al., 2022). DTW does not assume linear relationships but can capture nonlinear dependencies. DTW could be more robust in aligning non-stationary time series data with irregular time intervals, which is common in mental health monitoring. Moreover, it allows for flexible alignment of two time series by warping them, as symptoms may not occur at the same time for every individual. The analysis of individual level data has the potential to study the dynamics of each person's unique psychological process; such insights using intensive data monitoring are an important next step towards personalized psychiatry. Such findings are different from the results from epidemiological or traditional clinical data, which, although being of great importance for prevention strategies and policy, they offer little directions for a clinician who is sitting next to an individual patient. This personalized approach allows researchers and clinicians to develop and offer tailored interventions that focus on the specific needs of an individual patient. For example, if the individual data analysis of one patient shows that feelings of entrapment, hopelessness and suicidal ideation seem to continuously re-enforce each other, a clinician could, together with the patient, focus on an intervention specifically targeting these symptoms. The patient and the clinician can closely monitor the progress and modify the intervention if the results are not resulting in the expected outcome. Before this can be applied in daily clinical practice, several steps need to be taken. For one, the software collecting the data must work seamlessly. As stated above and described elsewhere, an important reason for the small sample size was that many patients experienced technical problems. This is demotivating for the patient, and has a negative effect on the quality of the data. Even when all prompts are received at the correct time, the continuous answering of prompts is likely to impact upon the way patients answer the questions. By not offering the same questions each time, but by randomizing the symptoms in the prompts, this can partly be mitigated.

9.5. Future directions

A possible next step would be to do comparable analysis on other intensive longitudinal datasets, to replicate, falsify or extend our findings. It would be interesting to see if in other samples negative mood symptoms such as depressed mood and entrapment also cluster over time for most patients. To study the dynamics over time, panel data can also be used opening the door for many more comparable secondary analysis (Freichel, Wiers, O'Shea, McNally, & De Beurs, 2023). By further exploring the similarities and differences in dynamics over time of symptoms, another building block towards a more formalized model of suicidal behavior becomes available (Millner et al., 2020). Insights from studies with empirical data such as ours can be used to test the validity of a computational model. For example, researchers used insights into the quick fluctuation of suicidal ideation over time as demonstrated with EMA data first as a building block of their model, and second as a benchmark for the validity of their simulations (Wang, Robinaugh, Millner, Fortgang, & Nock, 2023). An extended computational model based on the dynamical networks from our study can be used to derive testable hypothesis (Bringmann et al., 2022). For example, simulations based on the model can be applied to test the hypothesis that under stress symptoms that cluster over time tend to form an even more densely connected network. All this would help us further understand the complexity of suicidal behavior, with the ultimate aim to improve our prevention, assessment and treatment of suicidality and related behaviors.

Enriching the data set with psycho (social) and behavioral factors would offer a more complete picture of the multilevel interaction between all kinds of different factors (van der Wal et al., 2021). Ideally data would be collected using a combination of obtrusive and unobtrusive measure as well as external stressors, so that next to insights into psychological symptoms, we will have continuous data with regard to behavior factors such as sleep, movement and heart rate variability, as well as social media usage and proximity to others via blue tooth (e.g. via digital phenotyping (Jagesar et al., 2021)).

To implement individual networks such as the one in our study into clinical practice, the PREMISE method has been developed (Burger, Epskamp, et al., 2022). Although still in development, the method formally combines data driven personalized networks with case formulation. In our example, imagine that a patients discusses with the therapist that whenever he feels depressed, he finds himself quickly spiralling down, becoming even more depressed. Insight from his network based on DTW analysis might help the patient realize that his initial feelings of depression almost immediately activated rumination, feelings of worthlessness and entrapment cluster, starting a negative feedback loop that ultimately results in deterioration of mood. The combination of case formulation and data driven insights might help the patient and the therapist choose the best personalized treatment strategy (Burger, Epskamp, et al., 2022).

Although much work is to be done, to facilitate implementation of insights from dynamical networks in clinical practice, a freely available interactive web application (julianburger.shinyapps.io/PREMISE/), is being developed and tested, where you can construct an initial case formulation by drawing up the dynamical relationships between predetermined constructs in dialog with a patient. In the next step, individual EMA data of the patient can be uploaded to update this case formulation (see for detailed example Burger, Ralph-Nearman, & Levinson, 2022).

In sum, in this study we used dynamic time warping to better understand the co-occurrence of symptoms of suicide risk over time. An important message was that all individuals had different networks. These findings highlight the importance of adopting an individualized focus when assessing suicidality as advocated by current suicide prevention guidelines. Overall, 4 symptoms seem to cluster with suicidal ideation, namely entrapment, hopelessness, worrying and sad mood. Entrapment was often the central node, driving other symptoms within the networks, as was worrying. For most patients perceived burdensomeness was least central in the undirected and directed networks but for some, its role was more central. Findings are limited by the small sample size and the omission of psychosocial or behavior factors. Results offer a first step towards understanding the dynamics and interaction over time of symptoms for suicidal behavior. By using DTW to analyse individual-level data, one could identify specific triggers, stressors, or events that contribute to changes in suicidal ideation or related symptoms.

Contributors

The idea for the article was conceived by DdB, EG, WB and CN. WB, CN and DdB collected the data. WB and CN prepared the data for the current analysis. EG did the analysis. DdB, EG and ROC wrote the initial draft. All authors contributed to the writing of the manuscript and all authors agree with the final version.

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CRediT authorship contribution statement

Derek de Beurs: Writing – review & editing, Writing – original draft, Funding acquisition. **Erik J. Giltay:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Chani Nuij:** Writing – review & editing, Formal analysis, Conceptualization. **Rory O'Connor:** Writing – review & editing, Writing – original draft, Conceptualization. **Remco F.P. de Winter:** Writing – review & editing, Conceptualization. **Ad Kerkhof:** Writing – review & editing, Funding acquisition, Conceptualization. **Wouter van Ballegooijen:** Writing – review & editing, Funding acquisition, Conceptualization. **Heleen Riper:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors have no competing interests to declare.

Data availability

Data will be made available on request.

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