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PTSD Symptom dynamics after the great east japan earthquake: mapping the temporal structure using Dynamic Time Warping

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ABSTRACT

Background: After the Great East Japan Earthquake [GEJE], approximately 70,000 Japan Ground Self Defense Force [JGSDF] personnel were deployed, risking Post-Traumatic Stress Disorder [PTSD]. The network approach to psychopathology suggests that symptoms may cause and exacerbate each other, resulting in the emergence and maintenance of disorders, including PTSD. It is therefore important to further explore the temporal interplay between symptoms. Most studies assessing the factor structure of the Impact of Event Scale-Revised [IES-R] have used cross-sectional designs. In this study, the structure of the IES-R was re-evaluated while incorporating the temporal interplay between symptoms.
Methods: Using Dynamic Time Warping [DTW] the distances between PTSD symptoms on the IES-R were modelled in 1120 JGSDF personnel. Highly correlated symptoms were clustered at the group level using Distatis three-way principal component analyses of the distance matrices. The resulting clusters were compared to the original three subscales of the IES-R using a Confirmatory Factor Analysis (CFA).
Results: The DTW analysis yielded four symptom clusters: Intrusion (five items), Hyperarousal (six items), Avoidance (six items), and Dissociation (five items). CFA yielded better fit estimates for this four-factor solution (RMSEA = 0.084, CFI = 0.918, TLI = 0.906), compared to the original three subscales of the IES-R (RMSEA = 0.103, CFI = 0.873, TLI = 0.858).
Conclusions: DTW offers a new method of modelling the temporal relationships between symptoms. It yielded four IES-R symptom clusters, which may facilitate understanding of PTSD as a complex dynamic system.

Dinámica de los síntomas de TEPT después del Gran Terremoto del Este de Japón: mapeo de la estructura temporal mediante la Deformación Dinámica del Tiempo

Antecedentes: Después del Gran Terremoto del Este de Japón (GEJE, por sus siglas en inglés), se desplegaron aproximadamente 70,000 miembros de la Fuerza Terrestre de Autodefensa de Japón (JGSDF, por sus siglas en inglés), con el riesgo de sufrir un trastorno de estrés postraumático (TEPT). El enfoque de red de la psicopatología sugiere que los síntomas pueden causarse y exacerbarse entre sí, lo que da como resultado la aparición y el mantenimiento de trastornos, incluido el TEPT. Por lo tanto, es importante explorar más a fondo la interacción temporal entre los síntomas. La mayoría de los estudios que evalúan la estructura factorial de la escala Impact of Event Scale-Revised (IES-R) han utilizado diseños transversales. En este estudio, se reevaluó la estructura de la IES-R mientras se incorporaba la interacción temporal entre los síntomas.
Métodos: Usando la Deformación Dinámica del Tiempo (DTW por sus siglas en inglés), las distancias entre los síntomas de TEPT en la IES-R se modelaron en 1120 miembros del personal de la JGSDF. Los síntomas altamente correlacionados se agruparon a nivel de grupo utilizando análisis de componentes principales de tres vías DiSTATIS de las matrices de distancia. Los grupos resultantes se compararon con las tres subescalas originales de la IES-R utilizando un Análisis Factorial Confirmatorio (CFA).
Resultados: El análisis de DTW arrojó cuatro grupos de síntomas: intrusión (cinco elementos), hiperexcitación (seis elementos), evitación (seis elementos) y disociación (cinco elementos). El CFA produjo mejores estimaciones de ajuste para esta solución de cuatro factores (RMSEA = 0,084, CFI = 0,918, TLI = 0,906), en comparación con las tres subescalas originales de la IES-R (RMSEA = 0,103, CFI = 0,873, TLI = 0,858).

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关键词
PTSD; 动态时间规整; 事件影响量表修订版; 症状动态; 解离; 网络

HIGHLIGHTS

- Personnel from the Japan Ground Self-Defense Force responded to the aftermath of the 2011 Great East Japan Earthquake, putting them at increased risk of developing symptoms of Post-Traumatic Stress Disorder.
- In recent years, psychological research has focused increasingly on methods to map the ways in which symptoms of psychopathology cause and exacerbate each other.
- The Dynamic Time Warping algorithm seems to be an appropriate and useful tool to analyse the interaction between post-traumatic stress symptoms over time, especially if these are not instantaneous or linear. This can improve our understanding of psychopathology and help move towards personalized medicine.

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Conclusiones: La DTW ofrece un nuevo método para modelar las relaciones temporales entre los síntomas. Produjo cuatro grupos de síntomas de la IES-R, lo que puede facilitar la comprensión del TEPT como un sistema dinámico complejo.

东日本大地震后的 PTSD 症状动态：使用动态时间规整绘制时间结构

背景 ：东日本大地震（GEJE）后，部署了大约 70,000 名日本陆上自卫队人员 (JGSDF），冒着患上创伤后应激障碍（PTSD）的风险。心理病理学网络方法表明，症状可能相互引发和加剧，导致包括创伤后应激障碍（PTSD）在内的疾病的出现和维持。因此，进一步探讨症状之间的时间相互作用非常重要。 大多数评估事件影响量表修订版（IES-R）因子结构的研究都使用了横截面设计。 在本研究中，重新评估了 IES-R 的结构，同时纳入了症状之间的时间相互作用。
方法：使用动态时间规整（DTW），在 1120 名JGSDF中对 IES-R 上的 PTSD 症状之间的距离进行建模。使用距离矩阵的 Distatis 三向主成分分析，将高度相关的症状群体级别进行聚类。使用验证性因子分析 (CFA) 将所得聚类与 IES-R 的三个原始子量表进行比较。
结果：DTW 分析得出四个症状簇：闯入（五个条目）、高唤起（六个条目）、回避（六个条目）和解离（五个条目）。 与 IES-R 的三个原始子量表（RMSEA = 0.103、CFI = 0.873、TLI = 0.858）相比，CFA 对该四因素解决方案产生了更好的拟合估计值（RMSEA = 0.084、CFI = 0.918、TLI = 0.906）。
结论：DTW 提供了一种对症状之间时间关系进行建模的新方法。它产生了四个 IES-R 症状簇，这可能有助于理解作为一个复杂动态系统的PTSD。

In the aftermath of the Great East Japan Earthquake [GEJE] in 2011, which caused immense destruction and loss of lives, approximately 70,000 Japan Ground Self Defense Force [JGSDF] personnel were deployed as first responders. First responders to disasters are at an increased risk of developing Post-Traumatic Stress Disorder [PTSD] (Berger et al., 2012). As the JGSDF conducts yearly mental health assessments, this provides a novel opportunity to explore symptom patterns in responses to traumatic stress over time in a large dataset. In earlier studies, we reported on the prevalence of PTSD (Nagamine et al., 2020) and trajectories of symptom development in this population (Saito et al., 2022). Now, we wish to use this extensive dataset to garner a deeper understanding of patterns in symptom emergence, proliferation, and extinction that could otherwise go unnoticed.

PTSD is defined by a specific set of co-occurring symptoms, including intrusive memories of a traumatic event, and avoidance of stimuli related to this event (American Psychiatric Association, 2013; McFarlane, 1992). In most areas of medicine, the co-occurrence of symptoms can be explained by the presence of a latent biological disorder (Borsboom, 2017; Fried & Cramer, 2017). In this model, PTSD symptoms tend to co-occur because of their underlying common cause, the experience of a traumatic event (McNally et al., 2015). However, this latent disorder approach has been questioned in the field of psychopathology in recent years (Borsboom, 2017). Since attempts to find indices of latent disorders have largely failed, and there is often no method of diagnosing psychiatric disorders independently of their symptoms (Borsboom & Cramer, 2013), alternative models of psychopathology have been proposed.

Complex dynamic systems theory posits that psychiatric illness results directly from the causal interplay between symptoms, rather than each symptom independently being the direct consequence of a latent disorder. PTSD may be described as a hybrid model, where some of the symptoms are directly caused by a traumatic event, but the maintenance of the disorder is a result of the causal relationship between symptoms over time (Fried & Cramer, 2017). For instance, symptoms directly caused by the event, like insomnia, can cause or exacerbate other symptoms like concentration problems (Varkevisser & Kerkhof, 2005) or irritability (Edinger et al., 2004), which may in turn influence the expression of other symptoms down the line (Greene et al., 2018). If this emergence of additional symptoms exacerbates the severity of the initial insomnia, a feedback loop is created (McNally et al., 2015). This interplay between symptoms can be modelled in a dynamic symptom network (Greene et al., 2018). Previous literature mapping PTSD symptoms through network analysis has often relied on cross-sectional networks (Chen et al., 2022). However, as co-variation between symptoms may not be instantaneous, a cross-sectional network may not capture all relevant associations between symptoms. Incorporating the temporal dynamics into our understanding of PTSD may provide targets for treatment, as this may help us intercept the causal pathway between symptoms and thereby halt the maintenance or development of further symptoms (Hebbrecht et al., 2020).

An often-used method of modelling directed networks is the Multi-Level Vector AutoRegression [mlVAR] model. However, the mlVAR model assumes stationarity of data, meaning that the mean, variance, and autocorrelation of a variable do not change over time (Jordan et al., 2020). This assumption may often be violated in the repeated measurement of psychological processes, for instance as patients' symptoms improve over time during treatment. A longitudinal study, using mlVAR to model PTSD symptom networks in Israeli adults exposed to the Israel-Gaza war, found many spurious connections in the directed symptom network (Greene et al., 2018). These spurious connections may be an artefact of the mlVAR model not being suited for repeated-measures network analysis of non-stationary psychological processes.

A promising method for mapping the temporal relationships between symptoms and identifying clusters of co-occurring symptoms is Dynamic Time Warping [DTW]. DTW is a statistical method of finding patterns in time-series data, by identifying the optimal non-linear, shape-based alignment in two time-series. It can be used to identify and quantify co-variations between these time series, even if this co-variation is not instantaneous (Keogh & Pazzani, 2001) and may therefore be overlooked in cross-sectional analyses. DTW has been previously established as an excellent method for studying time-series data in a variety of fields that are not directly related to psychopathology, including movement (Gavrila & Davis, 1995), speech recognition (Amin & Mahmood, 2008), and gene expression (Aach & Church, 2001). In psychopathology, the time-varying distance between symptoms is assessed by calculating the DTW distance between each possible combination of two symptoms. The first studies using this technique to analyse time-series data in psychopathology have been conducted recently, estimating symptom networks of depression using DTW (Hebbrecht et al., 2020), analysing changes in the clustering of individual symptoms of depression after electroconvulsive therapy (Booij et al., 2021), and grouping mood symptoms in healthy controls and patients with bipolar disorder (Qian et al., 2022). DTW has not yet been applied to the analysis of the temporal interplay between PTSD symptoms.

In this paper, we aimed to assess whether DTW is a viable method of taking the temporal dynamics of PTSD symptom expression into account in creating symptom clusters. We used data from the Japanese version of a widely used questionnaire that measures subjective distress after a traumatic event, the Impact of Event Scale-Revised (IES-R) (Asukai et al., 2002; Weiss & Marmar, 1997). The DTW algorithm was used to calculate the covariation over time between symptom items within individuals. The resulting distances were used to create group-level network representations, and a novel DTW-based clustering of symptom items. Subsequently, we compared these DTW-based clusters to the original subscale structure of the IES-R. We hypothesized that the DTW-based clusters would at least include an intrusion and an avoidance cluster, as these symptom groups may represent different states of PTSD (Chiba et al., 2021) and may therefore be less likely to co-vary.

1. Methods

1.1. Participants

The participants in this study were selected from the previously described sample of 56,388 JGSDF personnel who responded to the GEJE (Nagamine et al., 2020; 2018; Saito et al., 2022). These first responders participated in annual mental health surveys for up to seven years after this complex natural disaster. Only the data gathered from two to seven years after the GEJE (2013–2018) were included in this study, as our analysis required individual item data and for the earlier measurement points only sum scores were available. To simplify understanding of our data, we refer to the measurement points reported in our study as measurement point 1 through 6. We included JGSDF personnel who scored above threshold for probable PTSD diagnosis (> 25 on the Impact of Events Scale-Revised [IES-R] in a Japanese sample (Asukai et al., 2002)) at any point during the two- to seven-year follow-up reported in this paper. The DTW technique is used to analyse change patterns, and at least four assessments were necessary to capture these reliably within participants. Therefore, we included only personnel who completed the annual mental health survey at minimally four out of the six measurement points.

1.2. Psychological measures

PTSD symptoms were assessed using the Japanese version of the 22-item IES-R, which has good test–retest reliability ($r = 0.86$, $p < .001$) and high internal consistency (Cronbach's $\alpha = 0.92$–0.95) (Asukai et al., 2002). The IES-R was completed at six time points within the scope of this study.

1.3. Demographic characteristics and predictor variables

Demographic variables and several variables related to deployment conditions were assessed at the one-year follow-up point after the end of deployment. Therefore, this information was compiled one year prior to the start of the follow-up period reported in this paper.

1.4. Data analysis

Baseline characteristics were compared between the current sample and all non-participating subjects from the complete dataset using chi-square tests. Next, we conducted an undirected DTW analysis, and clustered the symptoms based on the undirected DTW distances. Thus, symptoms within each cluster exhibited a tendency to fluctuate together over time, with simultaneous or lagged increases and decreases. Subsequently, we compared the resulting DTW clusters to the original IES-R structure using Confirmatory Factor Analyses. Finally, we conducted a directed DTW analysis, created symptom networks based on the undirected and directed DTW analyses, and identified symptoms with high in- and out-strength, modelling their influence within the network.

1.4.1 Undirected DTW analysis

We calculated the distance between each of the IES-R symptoms using the DTW technique. For a detailed explanation of the DTW algorithm, see Figure 1. This algorithm measures the similarity between two time series by creating a cost matrix *[panel C]* and finding the path from the lower left corner to the top right corner that has the lowest stepping cost *[panel G, H, and I]*. The total distance accumulated in this path is interpreted as the dynamic distance between the two time-series. For the current analysis, we limited the algorithm to looking one step ahead and backwards in the time-series through a 'Sakoe-Chiba' window band of 1. The 'symmetric2' step pattern was used to match the two sequences *[panel B]*, and distance was normalized based on the number of assessments within that individual. A distance measure was produced, where items with the best alignment (i.e. having a more similar slope and similar changes over time) resulted in the smallest distances. Therefore, the undirected DTW distance between pairs of symptoms is not only based on the cross-sectional (Euclidian) distance, but can also take into account the value of the symptom at the previous and next datapoints (1 assessment earlier = lag-1 backward, or 1 assessment later = lag-1 forward) (Giorgino, 2009).

1.4.2 Cluster analysis

The acquired distances from the undirected DTW analysis were used to create clusters of symptoms with a high likelihood of similar shapes in time within participants (i.e. co-occurrence of increases and declines within participants). The dynamic time warp distances between each symptom pair in each patient were grouped in a distance matrix containing 231 (i.e. $n*(n\text{-}1)/2$) distinct distances per patient, resulting in a total of 231 * 1,120 = 258,720 calculated 'dynamic time warp' distances. At the group level, the dynamics of individual symptoms were aggregated to yield systematic patterns over time across patients. The 1,120 distance matrices were analysed using the 'Distatis' three-way principal component analysis algorithm, from which the first three compromise factors were derived (i.e. three principal components (Hervé Abdi et al., 2005; Herve Abdi et al., 2012)), as explain the highest amount of variance. Each of the 22 IES-R symptoms were plotted on two x-y planes; one according to the first and second compromise factor and one according to the first and third compromise factor (see Figure 2). The coordinates of the observations on the compromise factors were used to plot the items so that the distances in the map best reflect the similarities between the change profiles of the items.

Based on these plots, the number of symptom dimensions that best fit the data was assessed, and IES-R symptoms were sorted into these clusters. We first estimated the optimal number of dimensions by use of the elbow method, based on the percentage of variance explained as a function of the number of clusters. The three compromise factors were subsequently analysed in a hierarchical cluster analysis. Furthermore, the silhouette method (Rousseeuw, 1987) calculates the average distance of each item to all the items in the same dimensions and to those in the nearest cluster, with a plot of the average scores over all items against the different number of dimensions. The number of dimensions yielding the highest average silhouette score is considered the best fit. Using the hierarchical 'Ward.D2' cluster analysis, the total within cluster variance is minimized, and dissimilarities were squared before cluster updating. The hierarchical clustering was visualized in a dendrogram, which represents the general distance between the dynamics of the 22 symptoms (see Figure 2).

1.4.3 Confirmatory factor analysis

The symptom clusters were then compared to the original symptom dimensions of the IES-R using Confirmatory Factor Analysis [CFA] at each measurement point. The best fitting model was chosen using four fit indices: the Comparative Fit Index [CFI], Tucker Lewis Index [TLI], the Root Mean Square Error of Approximation [RMSEA] and its 90% confidence interval, and the Standardized Root Mean Square of the Residual [SRMR] (Hu & Bentler, 1995). Best fit was determined by the highest CFI and TLI, and lower RMSEA and SRMR. To evaluate the fit indices, the following cut-off criteria have been chosen: for CFI and TLI, values of >0.9 indicate good model fit, 0.8–0.9 indicate acceptable fit, < 0.8 indicate poor fit; for RMSEA, values of <0.05 indicate close fit, 0.05–0.08 indicate adequate fit, > 0.10 indicate poor fit; for SRMR, values of <0.08 indicate acceptable fit.

1.4.4 Directed DTW analysis

Subsequently, a directed DTW analysis was completed utilizing the same DTW algorithm, albeit with an

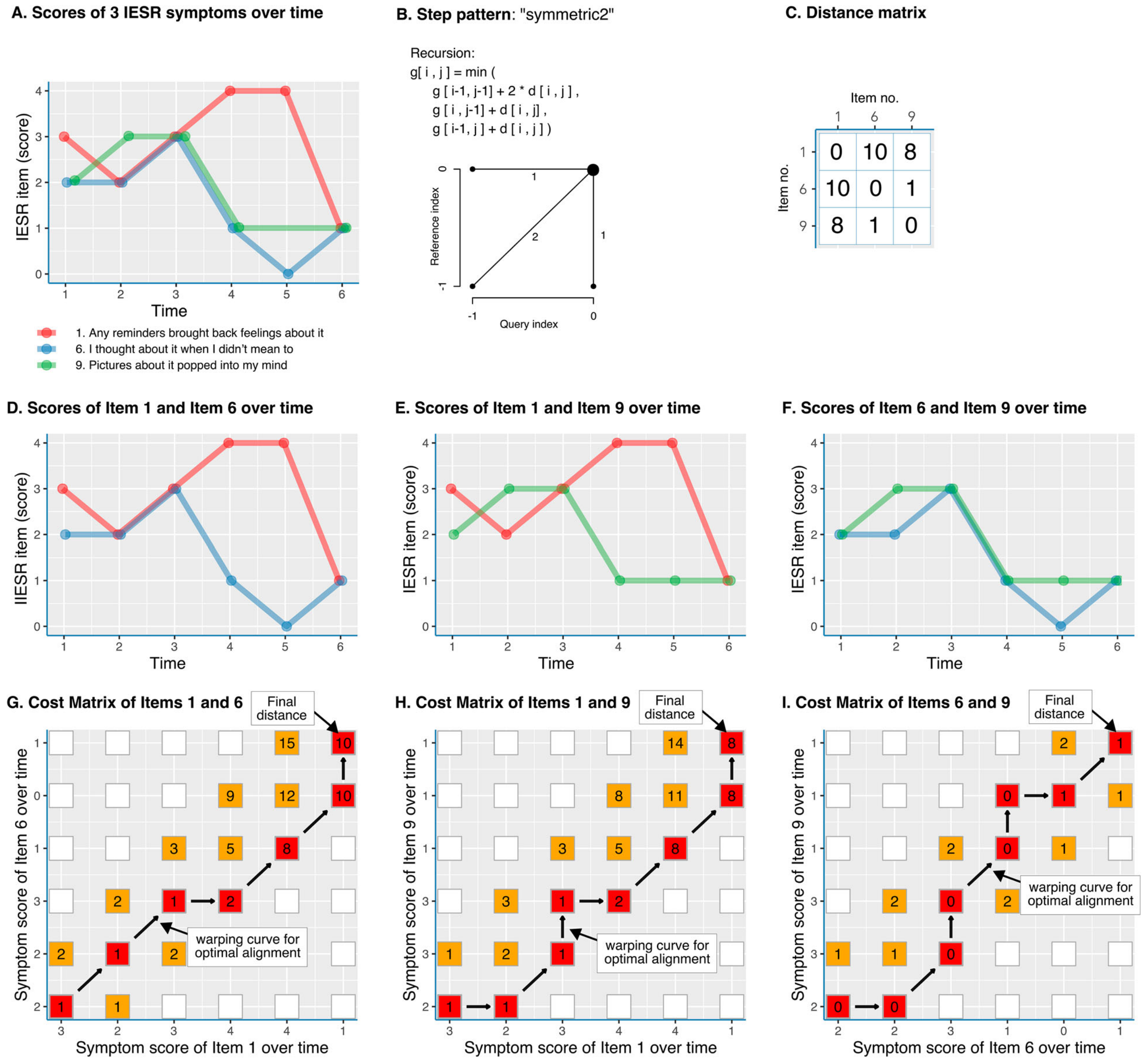

Figure 1. Explanation of Dynamic Time Warp algorithm. In panel A the (unstandardized) scores of these individual items 1, 6, and 9 are shown over time. We used the shape-based time-series clustering technique of DTW to yield the distance as a dissimilarity measure. The first step in DTW is creating a local cost matrix (CM), which in this case has 6 × 6 dimensions (as we included 6 assessments over time). In the second step, the DTW algorithm finds the path that minimizes the alignment between the two item scores by iteratively stepping through the LCM, starting at the lower left corner (i.e. LCMI1, 11) and finishing at the upper right corner (i.e. LCMI6, 61), while aggregating the total distance (i.e. 'cost'). At each step, the algorithm takes the step in the direction in which the cost increases the least under the chosen constraint. The constraint was the Sakoe-Chiba window of size one, meaning one time-point before and after the current assessment. The way in which the algorithm traverses through the LCM is dictated by the chosen step pattern, in this case the default 'symmetric2' step pattern (B). Parts (C). (D), and (E) explain the calculations of DTW distances for the three symptom pairs, yielding 10, 8, and 1 as their respective distances. We can conclude that items 6 and 9 share a more similar trajectory over time (with a distance of only 1), compared to the trajectory of item 1 (with distances of 10 and 8).

asymmetric Sakoe-Chiba band. This ensured the dynamic alignment between symptoms to be constricted to one direction later in time. This procedure parallels an analysis with the current (lag-0) as well as the next time point (lag-1). We calculated the distance from item A to B and the distance from B to A, which are inverse of each other. A positive relative difference from A to B indicates that changes in A precede similar changes of B, and this final distance (D) is calculated as: $(D_{A\text{->}B} - D_{B\text{->}A}) / (D_{A\text{->}B} + D_{B\text{->}A})$. This distance score ranges from −1 to 1, with 1 indicating that all changes in B exactly follow those of A in time (lag-1). When a lowering of symptom A was consecutively followed by lowering of symptom B, this was represented by an outgoing arrow from A (arrow-root) to B (arrowhead). For each of the participant, a directed distance matrix was calculated. Finally, all the 1,120 distance matrices were combined to yield standardized out-strength and in-strength centrality values, for which the confidence intervals were assessed through 5000 bootstraps. Symptoms with a significant 'out-strength' indicated that fluctuations

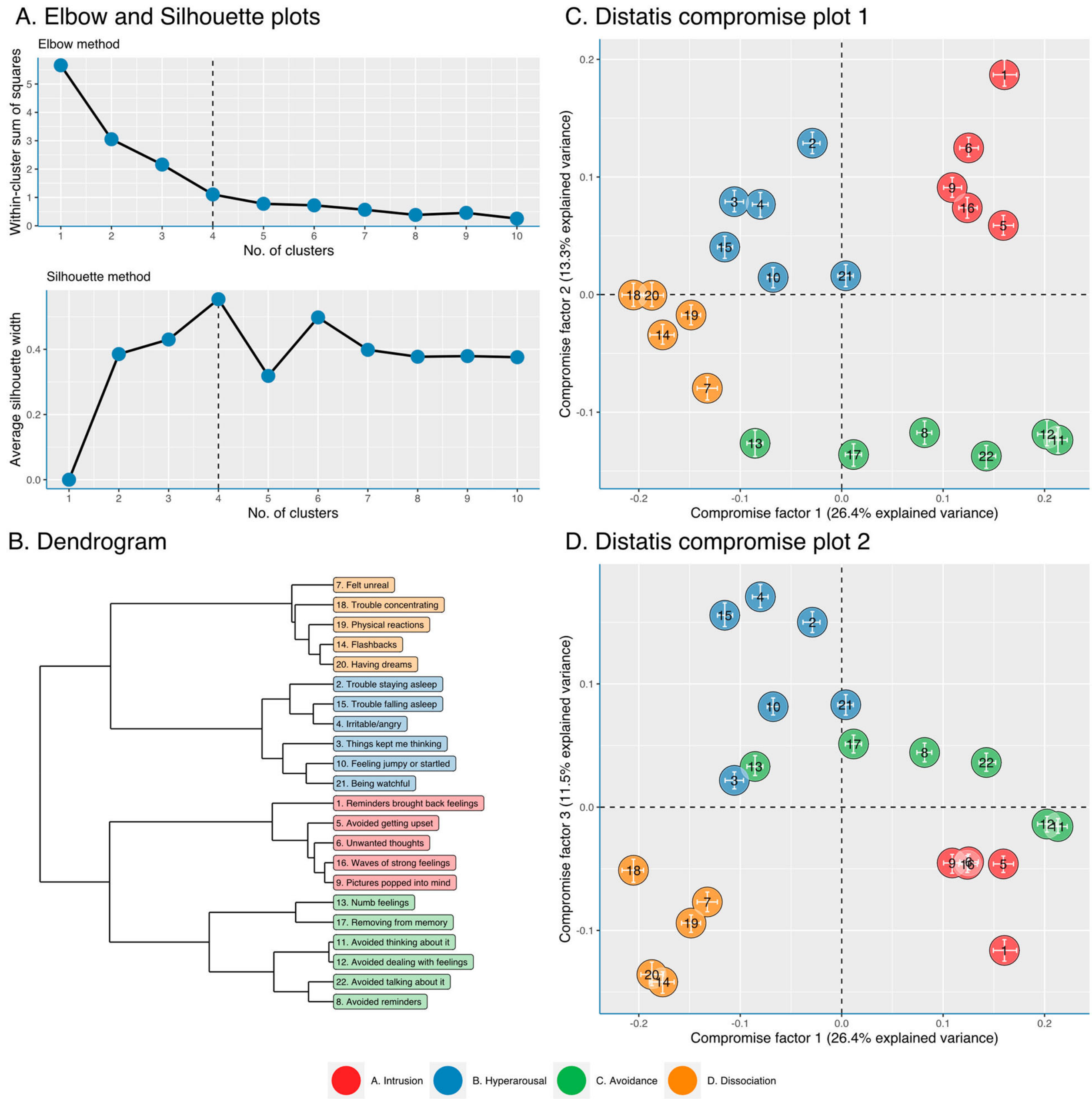

Figure 2. Hierarchical clustering procedure. Panel A shows the elbow and silhouette plots. The number of dimensions (symptom clusters) in the data was determined using the elbow plot, which was based on the eigenvalues in a downward curve based on three compromise factors, and the silhouette plot. Four dimensions yielded the highest average silhouette score and represented a slight curve in the elbow plot. Panel B shows a dendrogram of the hierarchical clustering procedure based on three compromise factors. Panels C and D show the compromise plots based on the Distatis analysis (three-way principal component analysis of the 1120 distance matrices). These represent the position of the 22 IES-R items in the compromise space using the first 2 compromise factors (panel C) and the first and the third compromise factor (panel D). The white horizontal and vertical error bars represent the 95% confidence intervals, estimated through bootstrapping with 500 resamples

in these symptoms tended to precede that of other symptoms, whereas changes in symptoms with significant 'in-strength' tended to follow similar changes in other symptoms.

1.4.5 Undirected and directed symptom networks

An undirected symptom network representation was created based on the Dynamic Time Warping distances. Only statistically significant edges are shown, with a smaller average distance than that of other pairwise DTW distances (by *t*-test for independent sample; $p < .05$). The standardized centrality of each of the 22 IES-R items was calculated and presented in a bar graph. A directed symptom network was also created. Edges reflect directed distances at the group level differed significantly from zero ($p < .05$). For each of the symptom items, in- and out-strength centrality were presented in another bar graph.

We used RStudio (R version 3.6.0; R Foundation for Statistical Computing, Vienna, Austria, 2016. https://www.R-project.org/), with main packages 'dtw' (version 1.20.1), 'parallelDist' (version 0.2.4), 'DistatisR' (version 1.0.1), 'qgraph' (version 1.6.2), and 'lavaan' (version 06-11) and for the CFA analyses.

2. Results

2.1. Sample characteristics

The demographic characteristics of the participants are summarized in Table 1. After selecting those who scored above threshold for probable PTSD (>25) on the IES-R at any of the measurement points, 1,674 cases qualified. Selecting those with IES-R data at four or more measurement points resulted in a final sample of 1,120 JGSDF personnel (22 female, 1.96%) aged 18–63 ($M = 35.2$, $SD = 9.30$). Mean IES-R score across the study was 15.3 ($SD = 15.1$). Differences between the population in our original dataset and the current study sample in demographic variables and predictors of PTSD can be found in Supplementary Table 1. The current study sample ('cases') were significantly more likely to be exposed to several risk factors (e.g. higher age, being personally affected by the disaster, and deployment-related circumstances) for symptomatic PTSD trajectories identified in a previous study on this dataset (Saito et al., 2022). The distribution of scores on each of the 22 items over time in the 1,120 participants are shown in Supplementary Figure 1, showing that Item 1 ('Reminders brought back feelings about it') was experienced relatively frequently, and Item 14 ('I found myself acting or feeling like I was back at that time') was a relatively rare symptom.

2.2. Dynamic time warping

Clustering on the basis of the prospective DTW analysis resulted in four symptom clusters that were labelled as: Intrusion (5 items), Hyperarousal (6 items), Avoidance (6 items), and Dissociation (5 items) (see Figure 2). The most important difference with the original subscale structure of the IES-R was the clustering of five symptom items from the original Intrusion, Hyperarousal and Avoidance subscales into an additional category. This new subscale consisted of the items 'I felt as if it hadn't happened or wasn't real', 'I found myself acting or feeling like I was back at that time', 'I had trouble concentrating', 'Reminders of it caused me to have physical reactions, such as sweating, trouble breathing, nausea, or a pounding heart', and 'I had dreams about it'. We named this symptom cluster the 'Dissociation' cluster, as it consists of items that reflect re-experiences, a lack of connection to the present moment or an elevated sense of presence in the moment of the traumatic event. In the literature, dissociation in response to psychological trauma is defined as a discontinuity in subjective experience, an inability to access information or control mental functions, or a sense of experiential disconnectedness (Cardeña & Carlson, 2011). We therefore consider the term 'Dissociation' fitting for the items in this symptom cluster, albeit with some caveats. Some important aspects of dissociation were not captured by the IES-R, and the symptom item 'I had dreams about it' does not neatly fit the definition.

Otherwise, only three other symptoms were sorted into a different cluster. The item 'I avoided letting myself get upset' clustered with other items in the Intrusion subscale, instead of its original place in the Avoidance subscale. The item 'I had trouble staying asleep' moved from the Intrusion subscale to the Hypervigilance cluster, where it joined the other sleep item 'I had trouble falling asleep'. The item 'Other things kept making me think about it' also clustered with the Hypervigilance items, instead of the Intrusion items. An interactive three-dimensional plot of the distances between symptoms, coloured by cluster, was also produced to aid visualization of the data [see Supplementary Figure 2, which can be downloaded at: https://osf.io/yhdw6].

Table 1. Demographics.

	n	%
Participants	1120	
Sex		
male	1098	98.0
female	22	2.0
Age		
<= 25 y	94	8.4
26–30 y	181	16.2
31–35 y	217	19.4
36–40 y	249	22.2
41–45 y	258	23.0
>= 46 y	121	10.8

Note: Participants with at least four completed measurement points and at least one IES-R score > = 25.

2.3. Confirmatory factor analysis

Cross-sectional CFA analysis yielded better fit estimates for the four-factor solution based on the DTW algorithm, compared to the original three subscales of the IES-R at each time point (see Table 2).

2.4. Network analysis

The DTW undirected and directed distances can be visualized using symptom networks. In this graphical representation, 'nodes' represent symptoms and 'edges' represent the (temporal) associations between them. In undirected symptom networks (see Figure 3) symptoms with similar dynamics in time result in smaller DTW distances which are visualized as thicker edges. The size of each node is proportional to the connectivity of that node. In directed symptom networks the direction of the lag-1 dynamic between

Table 2. Confirmatory Factor Analysis of remaining original sample ($n = 54{,}512$).

	Intrusion	Avoidance	Hyperarousal	Dissociation
1. Any reminder brought back feelings about it.	0.71			
16. I had waves of strong feelings about it.	0.71			
5. I avoided letting myself get upset when I thought about it or was reminded of it.	0.65	0.37		
6. I thought about it when I didn't mean to.	0.64			
9. Pictures about it popped into my mind.	0.65		0.32	
11. I tried not to think about it.		0.81		
12. I was aware that I still had a lot of feelings about it, but I didn't deal with them.		0.86		
17. I tried to remove it from my memory.		0.59		
22. I tried not to talk about it.		0.58		
8. I stayed away from reminders of it.		0.61		
15. I had trouble falling asleep.			0.71	
2. I had trouble staying asleep.			0.72	
14. I found myself acting or feeling like I was back at that time.				0.53
18. I had trouble concentrating.			0.49	0.50
10. I was jumpy and easily startled.			0.39	0.38
13. My feelings about it were kind of numb.		0.33		0.31
19. Reminders of it caused me to have physical reactions, such as seating, trouble breathing, nausea, or a pounding heart.	0.44			0.45
20. I had dreams about it.	0.35			0.41
21. I felt watchful and on-guard.			0.32	0.39
3. Other things kept making me think about it.	0.37		0.37	0.37
4. I felt irritable and angry.			0.49	
7. I felt as if it hadn't happened or wasn't real.				0.33
SS loadings	3.30	3.26	2.28	2.10
Proportion var	0.15	0.15	0.10	0.10
Cumulative Var	0.15	0.30	0.40	0.50

pairs of symptoms are presented as an arrow, with the arrowroot representing the symptom which changes precede similar changes of the symptom at the arrowhead (see Figure 4).

In the undirected network, the items 3 ('Other things kept me thinking about it') and 12 ('I avoided letting myself get upset') were the most central symptoms, meaning that they had the smallest DTW distance to other symptoms. This means that their changes over time were most similar to those of other symptoms, and they may be more likely to co-vary with other symptoms. The lowest centrality items were item 13 ('My feelings about it were kind of numb') and 7 ('I felt as if it hadn't happened or wasn't real'), meaning that their changes over time were most dissimilar to those of other symptoms,

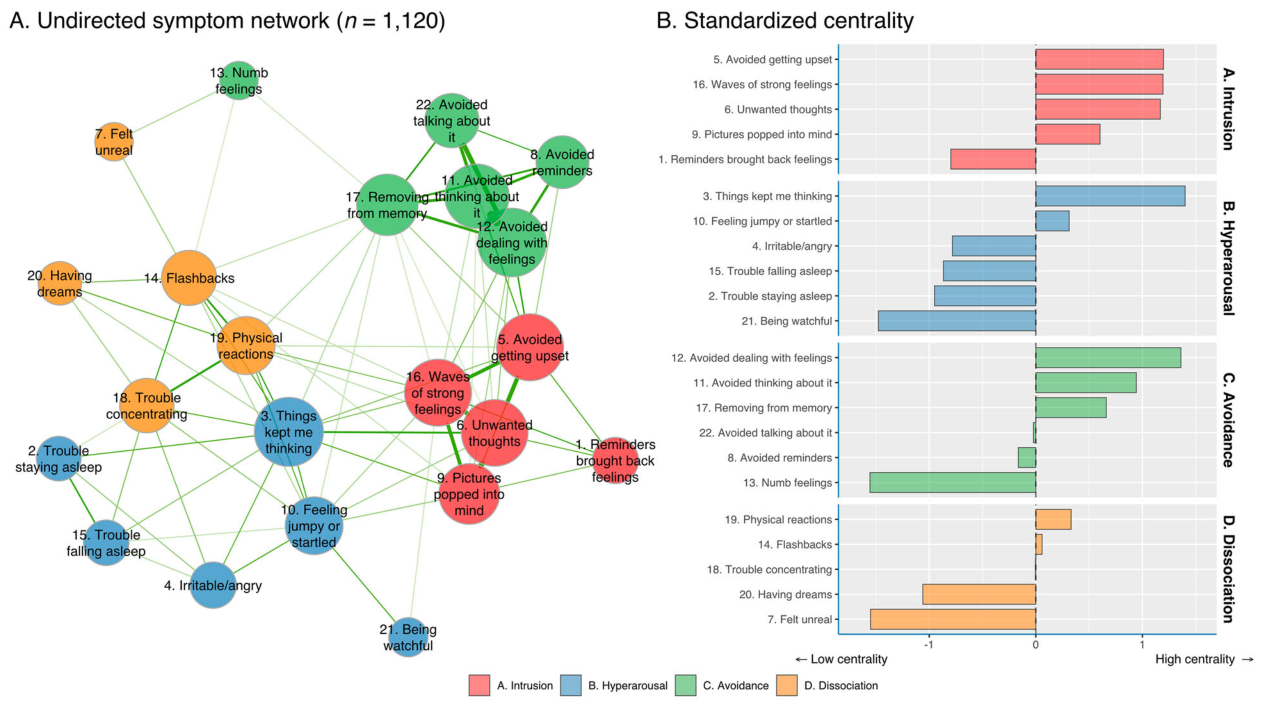

Figure 3. Undirected DTW symptom network. Items are represented as nodes and are colour-coded according to their cluster. Node sizes represent standardized centrality. Only statistically significant edges are shown, with a smaller average distance than that of other pairwise DTW distances (by t-test for independent sample; $p < .05$). Standardized centrality for each of the 22 items is presented in a bar chart.

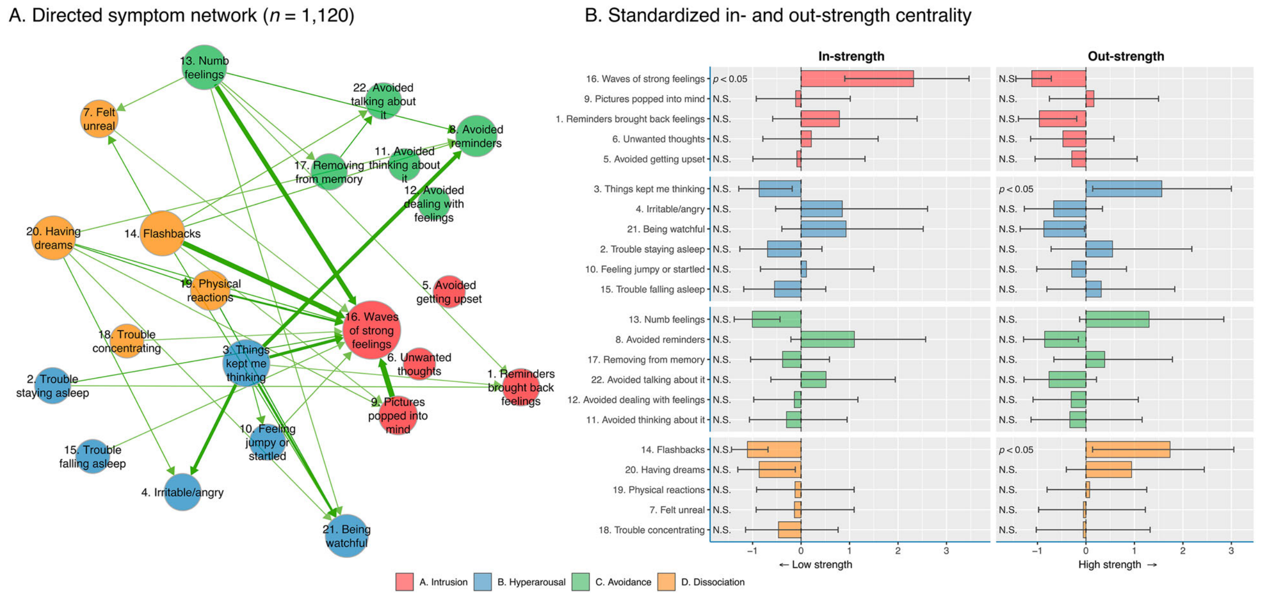

Figure 4. Directed DTW symptom network. Items are represented as nodes and are colour-coded according to their cluster. Node sizes represent the connectivity of that item (summing in- and out-strength centrality). Standardized in- and out-strength centrality for each of the 22 items is presented in a bar chart.

and they may vary most independently of other symptoms.

In the directed symptom network, the items 3 (‘Other things kept making me think about it’) and 14 (‘I found myself feeling or acting like I was back at that time’) showed significant out-strength, meaning that they significantly predicted the variation of other symptoms at later time points. Furthermore, item 16 (‘I experienced waves of strong feelings about it’) showed significant in-strength, meaning that its changes were significantly predicted by similar changes in other symptoms at a preceding time point.

3. Discussion

In this study we have used the Dynamic Time Warping algorithm to estimate the dissimilarity in the trajectories of individual PTSD symptoms over time in a sample of Japanese first responders to the 2011 GEJE. Using DTW, we have identified four symptom clusters, which largely corresponded with the original subscale structure of the IES-R. However, a new symptom cluster emerged consisting of five items that were originally distributed over the subscales. We refer to the new symptom cluster as the ‘Dissociation’ cluster. The subsequent CFA analyses showed that this four-factor structure fitted our data better than the original three subscales of the IES-R.

The original IES, the precursor to the IES-R, only consisted of an ‘Avoidance’ and an ‘Intrusion’ subscale (Horowitz et al., 1979). As the definition of PTSD was broadened to include ‘Hyperarousal’, items measuring this third subscale were added to the IES-R (Morina et al., 2010). Since then, many have investigated the factor structure of the IES-R and its translations using CFA. In these studies, different symptom clusters have been identified. One study on the general population in Iran during the coronavirus disease 2019 [COVID-19] pandemic (n = 500) showed support for the original three-factor structure of the IES-R (Sharif Nia et al., 2021). Four factors were identified in a sample (n = 174) of survivors of a fire and a sample (n = 562) of university students from Peru (Gargurevich et al., 2009), adding a ‘Sleep Disturbances’ cluster. These same four clusters were also found in a large sample (n = 3622) of Chinese earthquake victims (Wang et al., 2011). A large study (n = 4167) involving those with traumatic experiences from the war in Yugoslavia resulted in five clusters: adding ‘Numbing’ to the previously mentioned four (Morina et al., 2010). Larger samples tended to yield more IES-R symptom clusters, which could reflect increased power to detect detail in clustering as sample size increases. The current study included a relatively large sample, and comprised multiple measurements per participant, thereby also facilitating a large amount of detail in the clustering. We found slightly different clusters than in these previous cross-sectional studies, which may be due to the incorporation of the temporal symptom dynamics into our analysis. In addition to the new ‘Dissociation’ cluster, an important difference was that in our study the items related to sleep disturbances clustered with the ‘Hyperarousal’ subscale, instead of forming a separate symptom cluster.

Our CFA showed that the new DTW-based symptom clustering fitted our data better than the original IES-R subscales. Correctly clustering symptoms into subscales is important, as symptom clusters may respond differentially to various predictors or treatment. The items that were sorted into the new 'Dissociation' cluster through our DTW analysis were originally spread out over the other three subscales. If these items would, for instance, react particularly well to a certain treatment or be susceptible to a certain trigger, the effect is diluted and might go unnoticed if these items are distributed over the subscales. We have found the clustering identified through our DTW analysis to consistently fit our data better than the original subscales of the IES-R at each measurement point, suggesting that the clustering is relatively stable over time. Future research may focus on whether these clusters are also stable across cultural and trauma-related backgrounds. Also, it may be important to determine whether these findings are stable across groups of first responders with differential longitudinal symptom severity outcomes, to investigate which symptom clusters may be important in disorder maintenance in the longer term. Moreover, according to complex dynamic system theory the maintenance of PTSD emerges from the complex causal interactions among its components. Repeated assessment of scores on the new four DTW-based symptom clusters may improve the assessment and follow-up of PTSD severity within individual patients over time.

The term dissociation refers to alterations in awareness in the context of a traumatic experience (Bryant, 2007). Research has increasingly linked dissociative disorders to trauma history (Spiegel et al., 2011), and substantiated the importance of the dissociative symptoms of depersonalization (feeling disconnected from one's body) and derealization (feeling detached from one's situation or surroundings) (American Psychiatric Association, 2013) as possible components of PTSD. Therefore, a dissociative subtype of PTSD was included in the DSM-5. However, as the IES-R was based on earlier versions of the DSM[34], no direct questions about current depersonalization or derealization were included. We will therefore compare the results of the current study to literature that uses the broader definition of dissociation. Notably, a recent meta-analysis of papers discussing the prevalence of dissociation in disaster survivors drew no conclusions, noting that the available studies had serious methodological limitations (Canan & North, 2019). Other available literature on dissociation and post-traumatic stress symptoms in first responders tends to focus on acute dissociation symptoms, and lack longer-term perspectives on the persistence of these symptoms. In first responders from Pakistan peritraumatic dissociation was found to be related to PTSD symptom severity, but post-disaster dissociation symptoms or IES-R item scores were not reported (Razik et al., 2013). This same association was found in police and first responders in the United States (Marmar et al., 2006), police officers in Brazil (Maia et al., 2011), and in Norwegian first responders to the aftermath of a terror attack (Skogstad et al., 2015). The current article may be an important contribution to this area, as it provides insight into dissociative symptoms years after the traumatic experience, and the 'Dissociation' cluster emerged from the data independently of theory or preconceived hypotheses.

Through our DTW analysis, we have incorporated the non-instantaneous co-variation of symptoms within individuals into the network, and found evidence that the symptoms of intrusive memories/rumination ('Other things kept making me think about it') and flashbacks ('I found myself feeling or acting like I was back at that time') may be the most important symptoms predicting changes in the severity of other symptoms. This may imply that these symptoms are especially important to target during treatment (McNally et al., 2015), though further research is needed to investigate this claim. As experimental studies using network analysis are lacking, the hypothesis that intervention on central nodes in the network may lead to improvement of other symptoms is theoretically appealing but needs further evidence (Bringmann et al., 2022). The symptoms we found to be most important predictors of variation in other symptoms are partially consistent with findings from a longitudinal network study that assessed centrality of symptoms and network structure over time in children and adolescents exposed to an earthquake (Ge et al., 2019), where emotional reactivity to reminders and flashbacks were consistently central symptoms in the network over time. However, this was assessed by comparing cross-sectional networks at different time points, and not by using a directional network approach. Another longitudinal study, using IES-R data and a cross-lagged panel network model, identified different symptoms as having the highest in- and out-strength. Hyperarousal symptoms were found to have the greatest out-strength, and avoidance symptoms to have the greatest in-strength in a sample of war survivors from Balkan countries. However, this paper used only two measurements, one year apart (Schlechter et al., 2022). In the previously mentioned longitudinal study modelling PTSD symptom networks in Israeli adults exposed to the Israel-Gaza war using an mlVAR model, different results were found (Greene et al., 2018). In that study, the temporal network showed sleep disturbance, and loss of interest as having the highest in-strength and restricted affect, blame, negative emotions, and avoidance of thoughts as having the highest out-strength. The use of an Ecological Momentary Assessment [EMA] module was one of the strong points of that study. However, as the directed network included many spurious connections, the results on in-strength and out-strength of symptoms may be influenced by the introduction of colliders through mlVAR. DTW may be a better way to model these networks, as it is able to address within- and between-subjects variation separately, and less vulnerable to the effects of colliders that could potentially yield spurious negative connections between symptom nodes (Greene et al., 2018). Furthermore, the directed mlVAR is only able to assess either simultaneous or lagged relationships, and DTW is able to include both simultaneous and lagged co-variation in a directed analysis. Further studies are needed that directly compare mlVAR and DTW models in the same sample, to assess the probability of spurious connections in both models. Furthermore, the DTW algorithm is capable of modelling networks based on a single person's symptom dynamics, facilitating personalized medicine (Hebbrecht et al., 2020).

In our opinion, a strong point of the current study is the application of the novel DTW technique to a large Asian dataset including four to six repeated measurements per participant. We have provided evidence that the DTW technique is appropriate and valuable to increase our understanding of the temporal dynamics of PTSD symptoms. We have also included a directed symptom network, in part as a proof of principle of DTW's utility in creating directed symptom networks. However, as there was only one measurement point per year, these findings should be interpreted cautiously. Symptoms typically interact and co-vary in much shorter timeframes, and in this study we are unable to report on those dynamics. Additionally, this temporal sparsity of the data could be a factor in the large confidence intervals we found for symptoms' in- and out-strengths. In future research, it would be interesting if the DTW algorithm could be applied to datasets containing more frequent and numerous measurements, such as those collected using EMA sampling or other digital health technologies (Shiffman et al., 2008). Furthermore, the IES-R is not a diagnostic measure of PTSD but a subjective measure of severity of distress caused by traumatic events. We can therefore draw only tentative conclusions about the co-occurrence of PTSD symptoms. Another limitation of the current paper is the limited number of women in our dataset (> 2%), which is reflective of the low number of women in the JGSDF, and their likelihood of being assigned more supporting roles and not being deployed to disaster regions (Nakagawa, 2019). Additionally, as this is the first use of DTW to analyse the temporal dynamics of PTSD symptoms, it is possible that the findings presented here are unique for the Japanese population, owing to cultural phenomena. It is also unknown whether these results are generalizable to other trauma exposures. Therefore, we encourage the replication of this analysis in other cohorts, including people with different cultural backgrounds and a larger proportion of women, and with different exposures.

DTW is a useful tool for assessing PTSD as a complex dynamic system, and tracking and visualizing non-linear and non-instantaneous symptom covariation. It can help increase our understanding of the symptom structure of PTSD both on the individual and on the group level, which may help research and clinical practice and facilitate a move towards personalized medicine. In first responders, dissociative symptoms that occur after the potentially traumatic experience may play an important role in post-traumatic stress symptom burden.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The data that support the findings of this study are available from the corresponding author, [AVS], upon reasonable request.

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