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Examining Dynamic Symptom Associations

The Cases of Post-traumatic Stress Disorder and Repetitive Negative Thinking

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At the end, what stays, what matters, what is important, is the (social) *network*!

"*It always seems impossible until it's done.*"

Nelson Mandela

Author Contributions

In this cumulative thesis, I present the results of my doctoral research, which was conducted under the supervision of Prof. Dr Thomas Ehring at the LMU Munich. The results of my research have been published or have been submitted for publication in international peer-reviewed journals. The authors' contributions to each of them are as follows:

Study I

Stefanovic, M., Ehring, T., Wittekind, C. E., Kleim B., Rohde J., Krüger-Gottschalk, A., Knaevelsrud, C., Rau, H., Schäfer, I., Schellong, J., Dyer, A., Takano, K. (submitted). Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors.

This chapter is a pre-copyedited version of a submitted article.

M. Stefanovic, T. Ehring, K. Takano, C. Wittekind developed the current research question and design. Data were partly taken from existing studies by J. Rohde, B. Kleim, A. Krüger-Gottschalk, C. Knaevelsrud, I. Schäfer, and T. Ehring. Data collection was performed by R. Heinrich, J. Schellong and A. Dyer. K. Takano and M. Stefanovic performed the data analysis and interpretation. M. Stefanovic drafted the manuscript, and all co-authors, provided critical revisions. All authors approved the final version of the manuscript for submission.

Study II

Stefanovic, M., Takano, K., Wittekind, C. E., Ehring, T. (submitted). Temporal and contemporaneous networks in Posttraumatic Stress Disorder (PTSD).

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M. Stefanovic, T. Ehring, K. Takano and C. Wittekind developed the study concept and design. Data collection was performed by M. Stefanovic and C. Wittekind. K. Takano and M. Stefanovic performed the data analysis and interpretation. M. Stefanovic drafted the

manuscript, and K. Takano, T. Ehring and C. Wittekind, provided critical revisions. All authors approved the final version of the manuscript for submission.

Study III

Werner, G.G, Göhre, I., Takano, K., Ehring, T., Wittekind, C., E., Stefanovic, M. (submitted). Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

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Study IV

Stefanovic, M., Rosenkranz, T., Ehring, T., Watkins, E. R., Takano, K. (2021). Is a High Association Between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience-Sampling Data. *Clinical Psychological Science*, https://doi.org/10.1177/21677026211009495.

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T. Ehring developed the study concept and design for Study 1, and T. Ehring, T. Rosenkranz, and E. R. Watkins developed the study concept and design for Studies 2 and 3. Data collection for Studies 2 and 3 was performed by T. Rosenkranz. K. Takano and M.

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Abstract

Conceptualization of mental disorders and changes in their diagnostic criteria have been present in research and practice for a long time. Recently, network analysis has been suggested as an alternative approach to explore the emergence of mental disorders. Namely, according to the network approach, symptoms and their associations are crucial for the development and maintenance of mental disorders. Estimated symptom networks provide an insight into the set of symptoms that characterize certain disorders and can help identify the core symptoms of the specific disorder, such as post-traumatic stress disorder (PTSD).

The first evidence of the presence of post-traumatic stress symptoms comes from a few thousand years before Christ. Nevertheless, PTSD was first included in the diagnostic classification system in 1980. To date, there are still ongoing debates related to the number and types of symptoms that should be included in the diagnostic criteria. Those debates are best reflected in the different diagnostic criteria for PTSD in the current versions of the two major diagnostic systems: the fifth version of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) and the eleventh version of the International Classification of Diseases (ICD-11).

According to the most recent meta-analysis, since the first PTSD network study in 2015, more than 70 cross-sectional studies have been identified across non-clinical, subclinical, and clinical samples (for detailed information about these studies, please see: Isvoranu et al., 2021). Overall, there were inconsistent findings, which could be attributed to the heterogeneity of the sample. Furthermore, in contrast to cross-sectional studies, only a few studies investigated temporal dynamics between PTSD symptoms within a day using the experience sampling method (ESM; e.g., repeated, daily, symptom assessments via smartphone).

Next to network approach which generally investigates symptom interrelations, it is also possible to examine specific association by focusing on the specific symptoms and/or processes. For example, the association between repetitive negative thinking (RNT) and negative affect (NA) was found across different mental disorders, including PTSD. There is an emerging question whether based on this association, it is possible to identify people of risk for psychopathology.

This dissertation includes four empirical studies that address several issues. First, **Study I** tested whether trauma type is one of the potential moderators that could explain inconsistent findings in PTSD cross-sectional network literature to date. Specifically, it was investigated whether characteristics of the two trauma types (type I trauma = single event; sudden and unexpected, high levels of acute threat; N = 286 vs. type II trauma = repeated and/or protracted; anticipated; N=187) influence the symptom constellation in the cross-sectional PTSD networks across PTSD patients. Edges (symptom associations) that repeatedly emerged in the previous PTSD network studies were replicated. Furthermore, results showed that two networks globally differed. Additionally, specific edges (symptom associations) that differed between symptom networks of the two trauma types were identified. Results implicate that trauma type contributes to the inconsistent findings of the cross-sectional PTSD network literature to date.

Second, PTSD symptom dynamics within the day were investigated using the experience sampling method (ESM; intensive, repeated smartphone assessments) for 15 days in a row, four time per day. Namely, **Study II** was designed to investigate *temporal* PTSD networks (illustrating how symptoms influence each other at the subsequent assessment) and *contemporaneous* PTSD networks (illustrating how symptoms influence each other within the same assessment). This study focused on PTSD patients (N=48) who were in the diagnostic phase but had not yet started with the trauma focused treatment. Results implicated the

importance of estimating both contemporaneous and temporal networks, as they differed in important ways. In the temporal network, it was identified that changes in *hypervigilance* predicted changes in the most symptoms at the next assessment.

As the focus of the second study was on the within-day dynamics, items related to sleep disturbances were excluded since they only referred to sleep at night and were assessed just once in the morning. Therefore, **Study III** focused specifically on the temporal association of trauma-related sleep disturbances, namely insomnia symptoms and nightmares, on PTSD symptoms in the following day. This study analyzed the same sample as in Study II. Multilevel model analyses showed that insomnia and nightmares were significant predictors of PTSD symptomatology on the following day, but that this association was unidirectional, as PTSD symptoms did not significantly predict insomnia and nightmares.

Finally, Study I investigated generally interrelations between PTSD symptoms. In addition, it is possible to specifically examine dynamic symptom associations by focusing on the specific symptoms interaction and explore their predictive value. Therefore, **Study IV** used a statistical clustering algorithm, specifically focusing on the association between RNT and NA, in order to investigate the predictive value of this association. Study IV looked at three experience-sampling data sets across a young population (N=130; N=120; N=186;). The analysis showed that two groups of individuals were repeatedly identified. One group had a higher bidirectional association between RNT and NA (and also higher inertia) than the other group. Additionally, results implied that it is possible to identify individuals at risk of developing depressive symptoms during the 3-month follow-up based on the interaction between dynamic associations between RNT and NA and levels of NA over the experience sampling phase.

Lastly, this dissertation outlines limitations and as well as practical and methodical directions for future research in the ESM and network analysis field generally and for PTSD

in particular. Overall, the obtained results from this dissertation and the implications for future research should contribute to the general improvement of the diagnostic process and to treatment, specifically for PTSD patients.

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General Introduction

"The whole is greater than the sum of its parts." – Aristotle

There are many scientific discoveries that has led to the maintenance and the development of the civilization. For example, discovery of the DNA helped to understand and treat different disorders and definitely raised the questions what make us who we are? Which information are our genes hiding? Further, the greatest discoveries, which have saved many lives, *Penicillin* and vaccines, directed the research into the searching for the single causes of disorders and their effective treatments. Medical imaging, from X-rays, radiography to MRI scans (magnetic resonance imaging) allowed doctors and researchers to investigate beyond the body surface.

Those great discoveries indeed influenced the daily life, public health and as well the directions of the research in the different fields, including the psychopathology research. Indeed, in the 20th century many causes of different disorders were discovered and many treatments were developed (Heath & Colburn, 2000), yet attempts to find the single cause of many mental disorders remains elusive. As there is generally no unique answer, at least not to this date, to what causes mental disorders, researchers, practitioners, and patients and their relatives all have their own assumptions. For example, the majority of psychiatry patients (59%) in Nigeria believe that psychological illnesses emerge due to supernatural forces (Aghukwa, 2012). Further, many surveys in Western countries have shown that lay beliefs about the causes of mental disorders, specifically depression and schizophrenia, are mostly attributed to social factors and less to genetic factors (Link et al., 1999; Matschinger & Angermeyer, 1996). On the other hand, a former director of the National Institute of Mental Health (NIMH) in the United States stated that over a 1,000 published manuscripts and around $20 billion in investment in discovering the genetic factors responsible for depression have not made any progress in understanding or helping patients, as no single effect was

replicated in the large-scale analysis, with results showing that numerous reported associations were false positives (Border et al., 2019; Fried, 2021; Rogers, 2017).

Previous (un)successful research has therefore taught us that if we aim to progress we must move beyond researching isolated phenomena. It seems that research has gone as far as it can in analyzing isolated phenomena, and that *reductionism*, where we try to determine the characteristics of the whole system by looking into the single parts (e.g., looking for a specific gene or one single cause), has many disadvantages when it comes to a complex system, such as mental disorders (Fried, 2021). "*The whole is greater than the sum of its parts*" claimed Aristotle, the Ancient Greek philosopher. Another interpretation of this famous statement is that not only is the whole better than the sum of its parts, but also that the whole provides us with different information than the single components on their own. This phenomenon, that characteristics of the system as a whole are different than characteristics of the single parts, is called *emergence* and is known as a one characteristic of complex systems. One frequently cited example of this phenomenon is how neurons in human brains produce intelligence. This indicates that complex systems such as intelligence cannot be wholly explained by the elements where it originated. Unlike the case of different infectious diseases, in the field of psychopathology we do not have a single cause that indicates the presence (or absence) of an infection. And interestingly, even researchers in the medical field have given up on the unifactorial disorder model when it comes to chronic disorders, such as hypertension (Kendler, 2019, as cited in Haslbeck 2020).

Research has shown that there are different risk factors that increase the chance that a person will develop a mental disorder. On the other hand, there are protective factors that *decrease* the chance that an individual will develop a mental disorder (Rolf et al., 1992). Numerous risks and protective factors for different mental disorders have been found on different levels, such as biological, psychological, cultural, and social (Rolf et al., 1992). It is

clear that psychological disorders are influenced by different factors and that many variables on the different levels are interacting. Furthermore, there are many non-linear changes that occur, and that are influenced by different variables. This is recognized as *dynamics*, which is another characteristic of complex systems. Complex system science investigates how a large combination of the different parts, their interactions, and their mutual influences can organize and lead to the whole, characterized by phenomena called *emergence*, *dynamics*, *self-organization*, and *adaptation* (Thurner et al., 2018).

Recently, complex system science was recognized as an important approach for psychological research (Fried & Robinaugh, 2020; Guastello et al., 2008; Hayes & Andrews, 2020; Olthof et al., 2020; Richardson et al., 2014). Human behaviour, emotions, thinking, and decision-making are complex, and due to the different dependencies, relationships, interrelations, and influence of the environment, they are hardly ever completely predictable. The need to study single components at the same time as one studies the complex interactions between them was recognized in psychopathological research (Fried & Robinaugh, 2020). Psychopathological research has therefore made a shift from looking for the diagnosis to investigating the inter relations between the symptoms and thus observing a mental disorder as a complex system. On a more general level, the disadvantages of the traditional approach to defining disorders categorically by the presence of a combination of symptom criteria has become increasingly apparent, because of the problems of local independence and insufficient proof of assumed causes for all symptoms, as well as problems related to summation of the different symptoms (Berrios, 1996; Borsboom & Cramer, 2013; Fava, 2014).

Recently, network models have been proposed as an alternative approach to conceptualizing disorders, and network analysis has been used as one of the methods to study complex systems, such a mental disorders, in psychopathological research (Borsboom, 2017;

Borsboom & Cramer, 2013; Cramer et al., 2010). According to the network approach, symptoms and their interactions play a central role in the development and maintenance of mental disorders. This is consistent with the theory of cognitive behavioural therapy, which stipulates that mental disorders emerge as consequences of the inter-related associations between cognitions, emotions, and behaviour (e.g., Beck, 1967).

Network Analysis

The first evidence of the network theory originates from 1735. In that year, the mathematician Leonhard Euler found a solution to the mathematical problem known as the *Seven Bridges of Konigsberg*. The city of Konigsberg (now Kaliningrad in Russia) was on the river and included two islands that were connected with seven bridges. The task was to walk through the city by crossing each of the bridges just once. Euler proved that this was not possible, due to the special conditions which had to be satisfied, and developed the first postulates of graph theory, which is considered to be the first proof of the network theory (Alexanderson, 2006; Euler, 1956). Network analysis represents sets of different statistical techniques developed from network theory, and is widely applied in different fields, such as computer science, electrical engineering, biology, economics, finance, climatology, ecology, public health, and sociology. In this dissertation, it will be refered to "*psychological networks*" (a term retrieved from Epskamp, 2017), which consist of psychological variables rather than of concrete entities (e.g., social networks consist of people). As there is no defined structure for these networks, in this still developing phase of network science in psychological research, the network's structure is estimated from the data (Epskamp, 2017). In *psychological networks*, different variables (e.g., symptoms, mood, traits) are named *nodes* and the relations between them are named *edges* (Epskamp, 2017). Edges could be visually represented in different ways, with different colours and sizes. Usually, green (or blue)

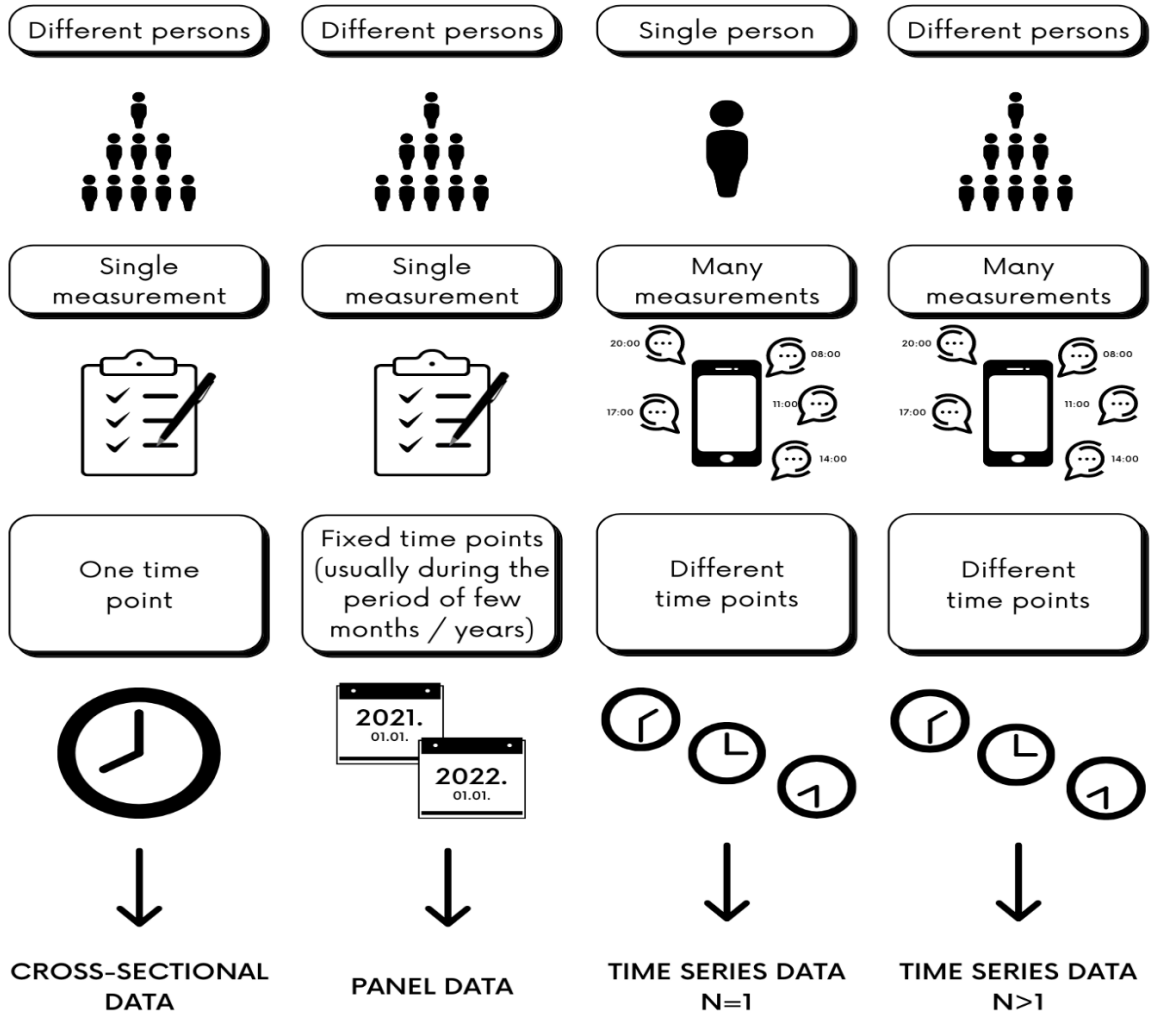
represents positive correlations and red represents negative correlations. Edges represent direct connections between nodes and the strength of those edges could be illustrated as stronger (visually presented as thicker) or weaker (visually presented as thinner). Additionally, directed and undirected edges can be differentiated. The former consists of an arrowhead, which indicates a one-way effect, and the latter is represented without an arrowhead, indicating mutual effects between two nodes. Psychological networks estimated on cross-sectional data are typically undirected networks, and networks estimated on time series data are typically directed networks (Epskamp, 2017).

Types of Analysis

Using network analysis, it is possible to investigate variables of interest on the cross-sectional data, and look into between-person associations. Cross-sectional analysis considers statistics for people at fixed measurement occasions (cross-sectional data, panel data, *see Figure 1*), usually called between-person measurements. Further, using network analysis, it is possible to investigate dynamics of daily momentary states, by using time-series data. This within-person analysis considers the effect on one specific person over time. The cross-sectional data and the time-series data will only align if the system is ergodic, which means that there are no between-person differences and that each person is completely identical with the other. These assumptions are never true in the field of psychological research, therefore both kinds of data are important for psychological research and, depending of the research question, could provide different information through the use of different analyses (Charness et al., 2012; Hamaker, 2012; Hoffman, 2015). For an overview of the different types of data, please see *Figure 1*.

Figure 1

Types of data



In the field of psychopathology, nodes are mostly presented with the different symptoms. The most popular method to estimate those networks is a pairwise Markov Random Field (PMRF: Lauritzen, 1996). A PMFR illustrates the network with undirected edges where two nodes are conditionally dependent, meaning two nodes between which there is no connection are independent after conditioning all other nodes. Depending on the type of data, there are different PMRF models. For binary data, the *Ising model* is applied (van Borkulo et al., 2014), while for continuous or ordinal data that satisfy multivariate normal

density the *Gaussian graphical model* is applied (GGM: Costantini et al., 2015), where edges present partial correlations. Mixed graphical models can be used with categorical and continuous data (Haslbeck & Waldorp, 2015). Additionally, in cross-sectional networks, three node centralities are analysed: *strength*, *closeness*, and *betweenness*. Strength describes how one node is directly connected to other nodes; closeness indicates the inverse sum of the shortest paths from one node to all other nodes; and betweenness illustrates how important a node is in connecting other nodes (Epskamp, 2017). Since recent research has shown that betweenness and closeness are not stable and are less interpretable in the symptom networks, in the psychopathology research only strength centrality metrics are further interpreted (Bringmann et al., 2019).

Dynamic network models could be estimated using time-series data. In the time series data, responses are most likely dependent. The typical statistical method for estimating the relationships between symptoms is vector autoregression (VAR: Epskamp et al., 2018; Zivot & Wang, 2003). In lag-1 VAR models, each node is predicted by itself and by other nodes assessed at the previous assessment. Mostly, VAR was used to estimate *temporal* networks, where the nodes are predicted by the previous assessment. However, VAR models could be used to estimate *contemporaneous* networks, capturing the inter relations between the nodes that occur in the same window of measurements (Epskamp et al., 2018).

Experience Sampling Methodology (ESM)

Time series data, i.e., time-intensive, repeated measurements, can be obtained by using experience sampling methodology (ESM). ESM is an important assessment tool that helps researchers and practitioners to access different individual processes in a daily environment through multiple assessments over time (Trull & Ebner-Priemer, 2013). It is important to clarify the different terminology around this methodology. Experience sampling method (ESM) and ecological momentary assessment (EMA) are used interchangeably in the

literature. An additional term is ambulatory assessment (AA), which typically accesses biological and physiological variables such as heart rate, blood pressure, and cortisol activity (Trull & Ebner-Priemer, 2013).

The biggest advantage of the ESM approach is ecological validity in assessments of a person's daily life and environment. Data are usually obtained multiple times per day, allowing insight into the dynamics and the variability of experience. Furthermore, multimodal assessment is possible, of physiological, emotional, psychological, and behavioural data. In clinical psychology, ESM is useful for different purposes, such as investigating mechanisms and symptom dynamics, symptom predictions, and observing treatment effects, prevention, and intervention (Trull & Ebner-Priemer, 2013). The disadvantage of ESM is the internal validity, as it is hard to standardize the setting and reactivity effect. Even though the sampling period could be long, it is typically short (from one week to a few weeks), and therefore important life events which occur less frequently could be missed. Historically, different settings have been used for ESM, and these shifts have followed technological developments. Before 1990, paper questionnaires were used in conjunction with beepers that alerted participants when questions should be answered. That changed with the emergence of *portable digital assistants,* which were used until 2010 when they were replaced by mobile phones and smart phones. In the last years, the most commonly used technology for ESM has been email alerting, which uses email servers and smartphone applications (Myin-Germeys & Kuppens, P [Eds.], 2021).

The experience sampling method is a suitable approach to study symptoms or mood dynamics that vary across time (Kuppens et al., 2010). In one of the studies included in this dissertation (**Study IV**), the ESM approach was used to assess the dynamics between negative affect (NA) and repetitive negative thinking (RNT), as this reciprocal relation was found across various aspects of psychopathology.

Examining Specific Edge

Using ESM and network analysis is possible to investigate temporal associations between different symptoms and/or processes and to identify significant edges. Indeed, the following question is whether identified edges have a predictive value and whether same edges emerge in different subgroups of individuals. If research shows that specific edge has a predictive value for specific subgroups, that edge would be a promising target of preventive interventions. To date, there are several associations which have been found across various mental disorders, such as a reciprocal association between RNT and NA. It is important to investigate whether this association could be an early warning sign of psychopathology for the specific subgroup of the individuals. Therefore, **Study IV** explored whether dynamics between RNT and NA can be predictive of future psychopathology through the use of a statistical clustering algorithm.

While clustering analysis was applied on only two variables, it could be expanded to a larger number of variables and cover complex networks, which are the main focus of this doctoral dissertation.

More specifically, the focus of this dissertation is different network models, cross-sectional (**Study I**) and dynamic (**Study II**), particularly on the symptom networks of PTSD.

Posttraumatic Stress Disorder (PTSD)

First evidence of the consequences of traumatic events dates back more than 4,000 years to a war during the Third Dynasty of Ur in Mesopotamia (Ben-Ezra, 2002). The city of Ur was attacked and destroyed. Cuneiform inscriptions from the time testify to the terrible way that people felt after they had seen dead bodies and witnessed terrible crimes. Many centuries later, similar complaints were recognized in the aftermath of other wars. During the First World War, soldiers started to report different psychological problems, such as

nightmares, fatigues, and jumpiness. Those problems mostly occurred after soldiers were in close contact with explosions, therefore it was named *shell shock* (Jones & Wessely, 2005). *Shell shock* distinguished between somatic problems, such as different physical wounds on the body, and psychological complaints. However, it was a long time before psychological complaints were recognized and directly linked to traumatic events people had experienced. Post-traumatic stress disorder (PTSD) was first included in the diagnostic classification system in 1980 (DSM-III: American Psychiatric Association, 1980). The usefulness and validity of the diagnosis has been widely recognized. Nevertheless, there have been decades of debate regarding the formulation of this disorder and those debates are still ongoing. The first issue concerns the ambiguity in number and type of symptoms to be included in the diagnostic criteria (Hansen et al., 2015; Hyland et al., 2016; O'Donnell et al., 2014). The second issue is whether there should be one uniform definition for PTSD vs. separate disorders for simple or complex cases (McNally et al., 2015). In addition, the diagnostic criteria for PTSD have been changed in each revision of the DSM, and those revisions typically reflect the debate around controversial diagnostic issues.

The most recent versions of the two major diagnostic systems, the fifth version of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) and the eleventh version of the International Classification of Diseases (ICD-11; World Health Organization, 2021) propose very different approaches to the definition and diagnosis of PTSD. On one hand, the DSM-5 proposes one universal diagnosis of PTSD that comprises 20 different symptoms divided into four clusters: 1) persistent intrusive re-experiencing of the traumatic event (*intrusive memories*; *nightmares*; *flashbacks*; *emotional distress in response to trauma reminders*; *physical reactivity to trauma reminders*); 2) avoidance of trauma-related internal or external reminders; 3) alterations in mood and cognition (*deficits in recalling features of the traumatic event*; *negative assumptions about*

oneself or the world; *exaggerated blame of self or others*; *negative affect*; *diminished interest in activities*; *feelings of isolation*; *diminished positive affect*); and 4) hyperarousal/reactivity (*irritability or aggression*; *risky behaviour*; *hypervigilance*; *heightened startle reaction*; *concentration disturbances*; *sleep disturbances*). Those symptoms could be combined with a complex algorithm, allowing for very different constellations of PTSD symptoms (Galatzer-Levy & Bryant, 2013) and including overlap with other disorders (Mitchell et al., 2017).

On the other hand, the newly proposed criteria for PTSD for revisions to the 11th edition of the International Classification of Diseases (ICD–11) only include 6 symptoms (i.e., *distressing dreams*, *dissociative reactions*, *efforts to avoid thoughts or memories*, *efforts to avoid external reminders*, *hypervigilance*, and *exaggerated startle response*) to diagnose PTSD as the primary diagnosis (World Health Organization, 2021). However, the ICD-11 has also introduced a separate diagnostic category for complex PTSD, which comprises three core elements of PTSD: enduring disturbances in the domains of affect, self, and interpersonal relationships (World Health Organization, 2021). The jury is still out as to which approach is more valid and more useful from practical and theoretical perspectives.

Since previous research has showed that there is a numerous way to have PTSD (Galatzer-Levy & Bryant, 2013), the logical question that followed was, which symptoms play a major role and which a secondary one. Using network approach, role of the specific symptom was explored. Namely, network presentation shows which symptoms are mostly connected with other symptoms and which symptoms are peripheral. Those network presentations are used as supplementary tool for the building the hypothesis which should be further explored in the causal research.

Network Perspective and Posttraumatic Stress Disorder

In the last decade, the network perspective has played an important role in psychopathological research. It was first investigated conceptually in 2008 (Borsboom, 2008)

and two years later it had its first empirical basis (Cramer et al., 2010). Five years later, the first publications about the network approach in the field of post-traumatic stress appeared (McNally et al., 2015; Schryver et al., 2015). Since then the network perspective has started expanding within PTSD network studies: according to the latest meta-analysis, more than 70 studies were identified (for detailed information about these studies, please see: Isvoranu et al., 2021).

Cross-sectional PTSD networks have been estimated across non-clinical populations (Armour et al., 2020; Benfer et al., 2018; Eddinger et al., 2020), refugees (Pfeiffer et al., 2019; Spiller et al., 2017), war-affected youth (Schryver et al., 2015), survivors of natural disasters (Ge et al., 2019; McNally et al., 2015; Russell et al., 2017) and terror attacks (Birkeland & Heir, 2017), military veterans (Armour et al., 2017; Lazarov et al., 2019; Mitchell et al., 2017; Moshier et al., 2018; Phillips et al., 2018; Simons et al., 2019; Stockert et al., 2018), adult survivors of childhood abuse (Knefel et al., 2016; McNally et al., 2017), treatment seeking patients (Djelantik et al., 2020; Fried et al., 2018), and patients exposed to traumatic events (Park et al., 2019).

Nodes mostly presented PTSD symptoms according to the fourth and fifth revisions of the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV; DSM-5: American Psychiatric Association, 1994; 2013) and according to ICD-11 (World Health Organization, 2021). Regardless of the sample differences, a recent systematic review and meta-analysis identified some edges that were robustly found: *hypervigilant* and *easily startled*; *nightmares* and *intrusive thoughts*; *internal avoidance* and *external avoidance*; *emotional numbing* and *feeling detached*; and *feeling detached* and *loss of interest*; and with *amnesia* as the least central symptom (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2020). Additionally, there are additional typically highlighted central symptoms that are closely associated with the other symptoms were *feeling detached*, *intrusive thoughts*, and

physiological reactivity. However, the main finding of the meta-analysis showed that there is no a specific single symptom that generally plays the most central role (Isvoranu et al., 2021). Despite some robust results, there are still inconsistent findings between PTSD network studies and the reasons for this inconsistency are still unclear. Furthermore, in comparison to cross-sectional PTSD network studies, to date, only a few studies have used the network approach to investigate longitudinal development of the symptoms (An et al., 2020; Bryant et al., 2017; Doron-LaMarca et al., 2015; Ge et al., 2019; Mancini et al., 2019; Papini et al., 2020) and temporal inter-relation between PTSD symptoms, namely *temporal* networks, using intensive ESM assessments (Greene et al., 2018; Hoffart et al., 2019; Reeves & Fisher, 2020). However, consistent with the cross-sectional studies, there is a huge heterogeneity regarding the type of sample.

Overall, many PTSD symptom networks were estimated, indeed some core edges were repeatedly replicated, however studies also provided inconsistent results. Emerging question which stays after numerous PTSD networks studies is what we learned from it? Which important information was provided and how we can use it in the praxis? PTSD network studies showed which symptoms are mostly connected with other symptoms and potentially have an important role in the maintenance and the development of the PTSD. Partly, problem of *reductionism* was solved, however it seemed that network approach didn't completely answer the question how specific disorder arises and that it was just on the half way of the solution. Some open questions still stayed. For example, current networks have just exploratory role, they provide insight into the symptom associations. However, there is still no evidence of causality, whether targeting the symptom which has most positive associations with other symptoms, also influence the severity of the related symptoms. Second, even though it was considered interrelation between symptoms, there are still other important factors on the different levels, such as environment, important life events, social

relations, biological factors, which could also influence the symptom network. There are some first ideas od the implementation of other important factors within the network, however there are many methodological challenges which have to be addressed, whether is possible to study those processes parallelly within the same network and how to control correlations within the same level, as naturally e.g., biological factors will cluster together rather that with environment. Additionally, there is a question whether one network could be estimated based on all individuals or there are significant individual differences based on the different levels, that is important to consider.

Emerging Challenges

Considering the findings of the PTSD network studies to date and network studies in general, several issues were addressed in this dissertation. First, although many cross-sectional PTSD network studies have been published, there are still some inconsistent findings. Indeed, symptom networks should be compared with the appropriate statistical tools, based on theoretical and empirical findings with the goal of exploring potential reasons for the inconsistent findings. Second, the within-a-day PTSD dynamic should be further explored by estimating *contemporaneous* and *temporal networks*, and focusing specifically on the clinical sample. Results could provide insight into the temporal symptom association and be the basis for experimental research that can further investigate the ability of a symptom to influence other symptoms. Third, it is important to separate between- and within-person measurements. Fourth, in order to prevent retrospective bias and to explore within-day dynamics it is necessary to assess PTSD symptoms in daily life, using ESM. Fifth, associations between RNT and NA have repeatedly been found across different mental disorders. Research should explore whether using statistical clustering on the association between RNT and NA is possible to discover individuals at risk for future psychopathology.

This thesis aimed to address these challenges.

Aim of the Present Thesis

In this thesis four empirical studies are presented. The major goal of this thesis was to investigate PTSD symptom dynamics and associations between RNT and NA. **Study I** tested whether trauma type is one of the potential significant moderators that may explain inconsistent findings in cross-sectional PTSD network literature to date. **Study II** focused on the within-day PTSD dynamic and the predictive role of the symptoms. **Study III** explored temporal associations of sleep related sleep disturbances, namely insomnia symptoms and nightmares and other PTSD symptoms. Finally, **Study IV** investigated the predictive value of the association between RNT and NA.

Study I

Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors

Stefanovic, M., Ehring, T., Wittekind, C. E., Kleim B., Rohde J., Krüger-Gottschalk, A., Christine Knaevelsrud, C., Rau, H., Schäfer, I., Schellong, J., Dyer, A., Takano, K. (submitted). Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors.

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M. Stefanovic, T. Ehring, K. Takano, C. Wittekind developed the current research question and design. Data were partly taken from existing studies by J. Rohde, B. Kleim, A. Krüger Gottschalk, C. Knaevelsrud, I. Schäfer, and T. Ehring. Data collection was performed by R. Heinrich, J. Schellong, A. Dyer and M. Stefanovic. K. Takano and M. Stefanovic performed the data analysis and interpretation. M. Stefanovic drafted the manuscript, and all co-authors, provided critical revisions. All authors approved the final version of the manuscript for submission.

Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors

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Abstract

Network analysis has gained increasing attention as a new framework to study complex associations between symptoms of post-traumatic stress disorder (PTSD). A number of studies have been published to investigate symptom networks on different sets of symptoms in different populations, and the findings have been inconsistent. We aimed to extend previous research by testing whether differences in PTSD symptom networks can be found in survivors of type I (single event; sudden and unexpected, high levels of acute threat) vs. type II (repeated and/or protracted; anticipated) trauma. Participants were trauma-exposed individuals with elevated levels of PTSD symptomatology, most of whom (94%) were undergoing assessment in preparation for PTSD treatment in several treatment centres in Germany and Switzerland (n = 286 with type I and n = 187 with type II trauma). We estimated Bayesian Gaussian graphical models for each trauma group and explored group differences in the symptom network. First, for both trauma types, our analyses identified the edges that were repeatedly reported in previous network studies. Second, there was decisive evidence that the two networks were generated from different multivariate normal distributions, i.e., the networks differed on a global level. Third, explorative edge-wise comparisons showed moderate or strong evidence for specific edges. Our findings suggest that trauma type contributes to the heterogeneity in the symptom network. Future research on PTSD symptom networks should include this variable in the analyses to reduce heterogeneity.

Keywords: PTSD, Trauma type, Network analysis, Bayesian Graphical Gaussian models

General Scientific Summary

Several studies have investigated symptom-to-symptom associations (i.e., symptom networks) in patients with post-traumatic stress disorder (PTSD) as well as other clinical and non-clinical populations. Results show large between-study heterogeneity in the shape of the network. Therefore, the current study aimed to investigate trauma type as a potential moderator of PTSD symptom networks, distinguishing between type I trauma (single event; sudden and unexpected, high level of acute threat) vs. type II trauma (repeated and/or protracted; anticipated). Findings suggest that the PTSD symptom network structure differs between type I and type II trauma survivors.

Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors

Posttraumatic stress disorder (PTSD) is a highly prevalent and disabling disorder with onset after trauma experiences. Since its introduction into the classification systems in 1980 (DSM-III: American Psychiatric Association, 1980), the exact definition and formulation of the disorder has been subject to considerable debate. According to the current version of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5: American Psychiatric Association, 2013), PTSD comprises 20 different symptoms that are combined by a complex algorithm, allowing for a multitude of symptom constellations (Galatzer-Levy & Bryant, 2013), and including some overlap with other disorders (Mitchell et al., 2017).

Recently, network analysis has been proposed as a novel approach to conceptualizing mental disorders (Borsboom & Cramer, 2013). Network analysis is a group of statistical techniques that are used to investigate and visualize the co-occurrence (typically correlation) between the phenomena of interest. The goal is to estimate the conditional dependence structure in the shape of a network diagram, with *nodes* representing each entity and with *edges* representing the associations between nodes. In psychopathological research, nodes typically represent individual symptoms of psychological disorders and edges are defined as (partial) correlations between the symptoms. In other words, the network approach informs which symptoms co-occur within a disorder and across disorders, and can therefore help to identify a core set of symptoms and their relationships that best characterizes a disorder such as PTSD.

Over the past five years, dozens of studies have been published on PTSD symptom networks in trauma survivors, including patients diagnosed with PTSD (Hoffart et al., 2019), adult survivors of childhood abuse (Knefel et al., 2016; McNally et al., 2017), military veterans (Armour et al., 2017; Mitchell et al., 2017; Stockert et al., 2018), survivors of terror

attacks (Birkeland & Heir, 2017; Mancini et al., 2019), survivors of natural disasters (McNally et al., 2015), refugees (Pfeiffer et al., 2019), and non-clinical populations (Benfer et al., 2018; Eddinger et al., 2020). A recent systematic review (Birkeland et al., 2020), as well as a recent meta-analysis (Isvoranu et al., 2021) identified edges that emerge robustly regardless of differences in culture, trauma type, and symptom severity (see also Fried et al., 2018). These include edges between the symptoms *hypervigilant* and *easily startled*; *nightmares* and *intrusive thoughts*; *internal avoidance* and *external avoidance*; *emotional numbing* and *feeling detached*; and *feeling detached* and *loss of interest*. In addition, *amnesia* is often recognized as the most peripheral symptom associated with few other symptoms in a network (Isvoranu et al., 2021).

Despite some consistent and robust aspects (e.g., re-experiencing amongst the core PTSD symptoms (Bryant et al., 2017; Haag et al., 2017)), researchers overall have concluded that there is large between-study heterogeneity in published PTSD symptom networks. For example, one of the earliest studies showed that the most central symptoms (i.e. the symptoms that are most closely associated with other symptoms) were hypervigilance, concentration impairment, physiological reactivity to trauma reminders, sleep disturbance, and flashbacks (McNally et al., 2015). However, this was not replicated in following studies (Birkeland et al., 2020). Analyses of multiple samples and datasets identified large random effect sizes on the correlational structure of the symptoms (Epskamp et al., 2021; Isvoranu et al., 2021). This raises the question of whether there are systematic differences in symptom networks between different subgroups of trauma survivors.

The current study focused on trauma type as a potential moderator of characteristics in PTSD symptom networks. It is conceivable that trauma type may be an important moderator, as it has been shown to have a significant impact on symptom severity, associations between symptoms, and prevalence of PTSD (Cloitre et al., 2009; Kelley et al., 2009; Kilpatrick et al.,

2013; Shevlin & Elklit, 2012; Stein et al., 2016), as well as the complexity of the symptom presentation (Cloitre et al., 2009; Cloitre et al., 2013). In addition, differences in symptom networks between survivors of different types of traumas were indeed found in two recent studies. In the first study, Benfer et al. (2018) computed PTSD symptom networks in female undergraduate students who had survived three different trauma types (i.e., motor vehicle accident, sexual assault, and sudden accidental or violent death of a loved one). Results showed a significant difference in the global edge strength between sexual assault and motor vehicle accident. In addition, visual inspections of the symptom networks for the different groups suggested that the network for sexual assault was most conceptually similar to PTSD as defined by DSM-5 (i.e., symptoms were most consistently linked to each other in a way that was similar to DSM-5 symptom clusters in this group) (Benfer et al., 2018). More recently, Macia et al. (2020) examined symptom networks of veterans with combat vs. non-combat index trauma. Their results showed some variability in the network related to presence and absence of combat experiences. However, no formal statistical tests were conducted on the between-network differences, and the conclusions were merely based on visual inspection of the relative network structure (Macia et al., 2020). In addition, the distinction between the different trauma types studied appeared to be somewhat arbitrary and not guided by theoretical ideas regarding differences in trauma type that could be related to differences in symptom presentation. For example, there is considerable evidence showing that sudden and unexpected traumatic events that are characterized by high levels of acute threat (e.g., accidents; single episodes of physical or sexual assault) may lead to different symptom presentations than repeated and/or protracted traumatic events (e.g., sexual and/or physical maltreatment in childhood) (Cloitre et al., 2013; Courtois & Ford, 2009). Research investigating the sequelae of type I vs. type II trauma has mainly focused on conceptual issues (e.g., whether or not different diagnoses are needed for classic vs. more complex

PTSD) (Maercker, Brewin, Bryant, Cloitre, Reed, et al., 2013; Resick et al., 2012) or the type of symptoms experienced following the different trauma types (Briere et al., 2008; Cloitre et al., 2009). However, to our knowledge, there has been no investigation about whether trauma type defined in this way is related to the co-occurrence of these symptoms, i.e., the PTSD symptom network structure.

The current study aimed to extend the promising findings on trauma type as a potential moderator for the structure of PTSD symptom networks (Benfer et al., 2018; Macia et al., 2020) in three ways. First, based on the theoretical and empirical findings, we used specific characteristics of trauma (single event; sudden and unexpected, high levels of acute threat vs. repeated and/or protracted, anticipated traumatic events) to distinguish between type I vs. type II trauma. We decided to use the current categorization as it has a strong theoretical and empirical basis (e.g., Cloitre et al., 2013; Courtois & Ford, 2009).

Second, we targeted mostly treatment-seeking trauma survivors in order to maximize the clinical relevance of our findings as non-clinical or analogue samples, such as a student population, which may have a different symptom distribution than a clinical population. Third, rather than relying on visual inspection of symptom networks, we used a particular statistical approach – the Bayesian method (Williams et al., 2020; Williams, 2021) – to estimate and compare the networks of different trauma types. This method has important practical advantages, such as being computationally more efficient and providing a higher power to detect network differences than the permutation-based test (van Borkulo et al., 2017) that has been used in the literature (Benfer et al., 2018; Fried et al., 2018).

Our analysis had three aims. First, we aimed to test whether edges identified in a relatively robust way in earlier studies would also emerge in the symptom networks in our study, irrespective of trauma type. Second, we hypothesized that the symptom network of type I trauma survivors shows a global difference to the network found in type II trauma

survivors, considering all possible edges (i.e., the entire covariance matrices). Third, we explored between-network differences regarding each edge to clarify which edges are characteristic of one of the networks but not the other.

Method

Particpants

Three datasets (total N = 586) were combined for the current study. The first dataset was taken from a published study (Krüger-Gottschalk et al., 2017), comprising 352 traumatized individuals attending different treatment centers specialized in trauma-related disorders across Germany (a subset of 32 participants were traumatized individuals recruited via newspaper ads; for details on recruitment see Krüger-Gottschalk et al., 2017). The second data set included 174 patients attending the Outpatient Treatment centre at LMU Munich. The third data set consisted of 60 patients attending the Outpatient Centre for Specific Psychotherapy at the Psychiatric University Hospital in Zurich, Switzerland. The same inclusion criteria were used across the three datasets: (a) participants had been exposed to at least one traumatic event in their lives, and (b) at least one month had elapsed since the trauma. Only those who met both criteria were invited to the assessments. 113 participants had to be excluded from the final sample as they did not provide sufficient data for the analyses (for details see Procedure below). Therefore, the final sample that was analysed and reported on in this article consisted of 473 participants, most of whom (94%) were attending a PTSD treatment center undergoing assessment prior taking up PTSD-specific treatment; however, they had not received any interventions, yet, at the time of assessment (for detailed sample characteristics, see Table 1).

Table 1

Sample Characteristics

Characteristics	Type I trauma survivors (n =286)	Type II trauma survivors (n = 187)
Age (years, M, SD)	37.27 (12.18)	37.14 (11.66)
Gender [a]		
Female (n, %)	162 (56.64 %)	125 (66.84 %)
Male	123	62
Education (n) [b]		
No qualification or only primary school	39	32
Middle school or equivalent	83	59
High school degree	75	42
University degree	73	25
Other	8	6
Type of traumatic events experienced (n) [c]		
Natural disaster	4	0
Accident	60	0
Physical assault	61	83
Sexual assault	74	96
Combat / Captivity	34	46
Life-threatening illness or injury	33	3
Sudden violent or accidental death	54	0
Any other very stressful event or experience [d]	58	30

Characteristics	Type I trauma survivors (n =286)	Type II trauma survivors (n = 187)
Recruitment		
Traumatized and attending assessment prior to PTSD treatment	260	181
Traumatized currently not seeking treatment	26	6

Note. *; [a] Missing for a participant (in type I trauma group); * [b] Missing for 8 participants in type I and for 23 in type II group; [c] A participant could indicate multiple traumatic events; [d] For example: being stalked, being a victim of intimidation by a criminal group, surviving from terroristic attacks.

Measures

The German version of the Life Events Checklist for DSM-5 (LEC-5: Weathers, Blake, et al., 2013) was used to measure trauma exposure. This self-report questionnaire assesses exposure to 16 categories of traumatic events and one additional item for any other exceptional stressful event. Participants were first instructed to indicate all applicable events among the categories. Next, participants specified whether they had personally experienced each indicated event or had witnessed it, whether they learned about the event happening to a close family member or a friend, whether it happened as a part of their job, or if they did not experience it at all. We used the extended version of the LEC, asking participants to provide a short statement about the most traumatic event among the events that they had experienced. They also provided follow-up information concerning the most traumatic event, such as how long ago the event happened, how they had experienced it, additional information about the content of the event, and whether this or a similar event had repeated. We grouped

participants into type I vs. type II trauma survivors on the basis of the most traumatic event reported (for the detailed criteria, see Procedure section).

The German version of the PTSD Checklist for DSM-5 (PCL-5: Krüger-Gottschalk et al., 2017; Weathers, Lit, et al., 2013) was used to assess PTSD symptoms. The PCL-5 consists of 20 items corresponding to the DSM-5 criteria for PTSD. Each item was rated for the intensity using a 5-point scale (0 = *not at all,* 4 = *extremely).* The PCL-5 has an established cut-off of ≥ 33, indicating clinically significant levels of symptoms (Krüger-Gottschalk et al., 2017; Weathers, Blake, et al., 2013). The PCL-5 has the following four subscales: Re-experiencing, Avoidance, Changes in mood and cognition, and Hyperarousal (Table S1). Internal consistency for the total PCL-5 score was excellent in the final sample (Cronbach's α =.93). When completing the PCL-5, participants were instructed to refer to the most traumatic event that they reported on the LEC (Weathers, Blake, et al., 2013).

Procedure

On the basis of the most traumatic event reported on the LEC, two independent raters classified participants as type I vs. type II trauma survivors. Both raters were trained clinicians, and the inter-rater reliability was excellent (Cohen's κ = 0.86). Any disagreements were discussed and resolved by the research team. Whenever available, clinicians who worked with the participants were also asked to rate the trauma type, which was used to verify the ratings provided by independent raters; this was possible for a subsample of *n* = 234. The rating procedure was organized as follows. First, we found that some participants (*n* = 57) did not provide a description of the most traumatic events on the LEC, so the data for those participants were not used in the analyses. Second, we checked whether the most traumatic events met the DSM-5 A criterion. The events that did not meet this criterion, or the events that could not be classified as type I or type II trauma, were also excluded from the analyses (*n* = 19). Third, we excluded the data from participants who reported no symptoms

of PTSD (as indicated by a PCL-5 total score of zero) or those who had not filled in the PCL-5 (n = 5). Finally, some participants (n = 32) had to be excluded from the analyses as they did not provide sufficient data for the analyses. The final sample size was 473 participants, comprising 286 type I trauma survivors and 187 type II trauma survivors.

Statistical analyses

First, we estimated Gaussian graphical models, namely symptom networks, on the reported PTSD symptoms for type I and type II trauma sufferers. Each node in the networks represented one of the 20 PTSD symptoms measured by the PCL-5, and each edge represented a partial correlation between two given symptoms. The networks were estimated using the Bayesian method implemented in the R package, BGGM (Williams & Mulder, 2020). This package provides a Gibbs sampler to generate posteriors with the Matrix-F prior distribution as a flexible alternative to (inverse) Wishart priors. For each network, we drew 5000 posterior samples, with which we obtained the posterior means of each partial correlation and their 95% credible intervals (CIs). To determine the conditional (in)dependence (i.e., "existence" of an edge in a network), we used the Bayes factor (BF), indexing the strength of the evidence for the alternative hypothesis (i.e., the partial correlation is not equal to zero) relative to the null hypothesis (i.e., the partial correlation is equal to zero). We set the threshold as BF > 3, which is typically interpreted as good evidence in favour of the alternative[1](Kass & Raftery, 1995).

[1] We found that the use of another threshold, i.e., a posterior probability > 0.95 for the alternative hypothesis, led to a network structure similar to the used threshold of BF > 3 (Biel and Friedrich (2018); see also the supplementary materials and Tables S2 and S3). Naturally, a more conservative threshold prunes more edges; e.g., for the network of the Type-1 trauma survivors, the threshold of a posterior probability > 0.99 identified 26 "significant" edges, whereas the threshold of > 0.95 led to 32 edges. A more conservative threshold is, in general, better to control the false discovery rate, but the threshold of 0.99 could be too conservative given that this threshold is known to identify many fewer edges than the standard estimation approach using the regularization with the graphical lasso (Williams, 2021).

Second, we tested the differences in the network between type I and type II trauma survivors. To test the network-wide global differences, we performed a predictive check on the basis of the Jensen-Shannon divergence (JSD), which is known as a symmetric version of Kullback-Leibler divergence (Menéndez et al., 1997). In general, this test statistic represents the distance between two distributions. From posterior samples, a predictive distribution of JSD is produced, which serves as a reference to determine the predictive *p* value for the observed JSD. The hypothesized group equality (to be rejected) was tested with alpha = 0.05. Put differently, this test identifies whether the covariance matrices of type I and type II trauma survivors are generated from different multivariate normal distributions. As another test statistic, we also computed the sum of squared error for the partial correlation matrices (Williams et al., 2020). As one of the most important advantages, this predictive method allows for testing a global (not edge-specific) difference between the networks (Williams, 2021). Additionally, a simulation study showed that this method is less sensitive to unequal sample sizes between the compared groups than the permutation-based test (Williams et al., 2020).

Third, after establishing the global difference, we performed edge-specific comparisons using Bayesian hypothesis testing; here, a BF was defined as the strength of the evidence favouring the alternative hypothesis (H_1: the edge is not equal between Type-1 and Type-2 trauma sufferers) over the null hypothesis (H_0: the edge is equal between the two groups). The BF can be interpreted as follows: BF > 30 indicates very strong evidence, BF = 10–30 indicates strong evidence, and BF = 3–10 indicates moderate evidence for H_1. For each of the network estimations, we identified no convergence issues through visual inspections of the trace plots and auto-correlations, and effective sample sizes of the posterior samples. In reporting the results of the network analyses, we adhered to the reporting standards for psychological network analyses[2] (Burger et al., 2020).

[2] Most of earlier studies on symptom networks in PTSD have reported centrality indices. We therefore also provide centrality indices for the networks computed in this study in the supplementary materials (Figures S2 and S3), as they may be informative to see the relative importance of a node within a network. However, we decided not to interpret the centrality indices here because we see little or no additive value of the indices in the context of network comparison (Bringmann et al. (2019). Instead, we explored network differences for each edge. Given that a centrality is e.g., a sum of edge strengths per node, edge-wise comparisons would already suffice to clarify how and where two networks differ.

Results

Participants' Characteristics

We first tested potential differences in demographics between type I and type II trauma survivors (Table 1). Results showed no significant difference in age, $t(405.44) = 0.11$, $d = -0.01$, $p > .90$, but did show a significant difference in the gender distribution, $\chi^2 (1) = 4.33$, $p < 0.04$, which is consistent with the WHO report that women are more likely to report type II trauma than men (World Health Organization, 2019

Second, we tested whether groups differed regarding their PCL scores. Type II trauma survivors scored higher on the PCL total score as well as the four subscales than type I trauma survivors (Table 2). Within the whole sample, 313 individuals (type I: 173; type II: 140) reported clinically significant levels of PTSD symptoms as indicated by PCL scores above the cut-off of 33 (Krüger-Gottschalk et al., 2017). Individual item means (and correlations) can be found in Figure 1A (and in supplementary materials Tables S4 and S5).

Table 2

Means (SDs) of the PCL-5 Scores for type I and type II trauma survivors

Variable	Type I (n = 286)	Type II (n = 187)	t	df	p
PCL-5 total score	37.42 (19.22)	43.59 (17.04)	-3.66	429.91	< 0.01
Re-experiencing	10.35 (5.64)	11.65 (5.10)	-2.60	425.28	< 0.01
Avoidance	4.19 (2.54)	5.07 (2.42)	-3.82	410.49	< 0.01
Changes in mood and cognition	12.15 (7.36)	14.81 (6.54)	-4.11	429.47	< 0.01
Hyperarousal	10.73 (6.15)	12.06 (5.42)	-2.47	431.15	< 0.01

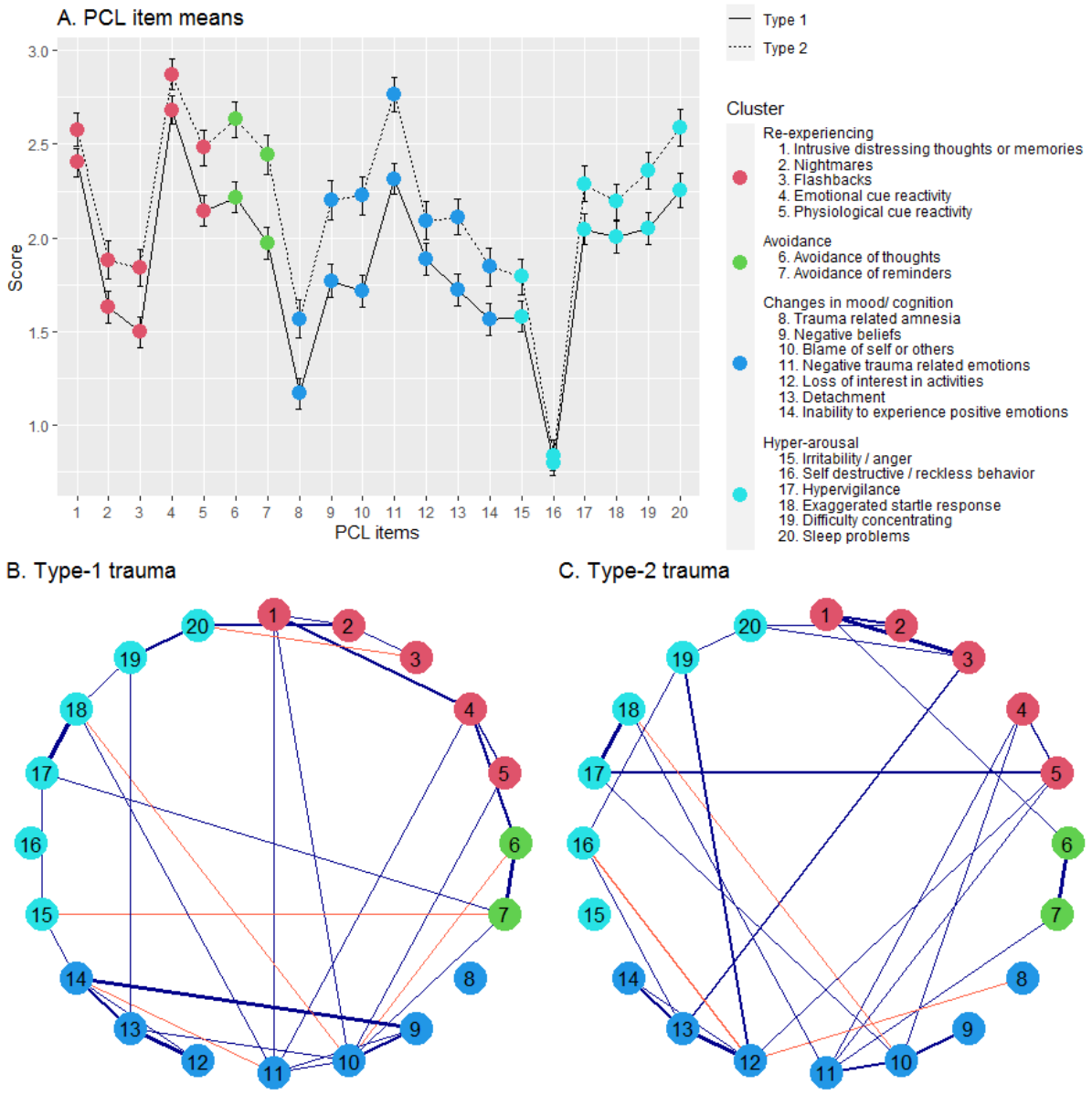
Note. PCL-5 = PTSD Checklist for DSM-5

Network Estimation for Type I and Type II Trauma

We estimated separate Bayesian Gaussian graphical models (partial-correlation networks) for type I and type II trauma survivors (Figures 1B and 1C). Both networks showed a strong edge between the items *hypervigilance* and *being easily startled*, which has repeatedly been found in previous network studies (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2021) Furthermore, other edges identified in the earlier literature emerged in both networks: *nightmares - intrusive thoughts*, *internal avoidance - external avoidance*, *emotional numbing - feeling detached*, *feeling detached - loss of interest*. These edges appear to be robust across different trauma types and other sample characteristics (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2021) and thus, may be interpreted as common features of PTSD-symptom networks.

Figure 1

Means of Individual PCL Items (with standard errors; Panel A) and Estimated Symptom Networks for Type-1 (Panel B) and Type-2 (Panel C) Trauma Survivors



Note. Red edges represent negative partial correlations, whereas blue edges represent positive partial correlations. The presented edges had BF > 3. See also supplementary materials (Tables S2 and S3) for the detailed estimates, such as the posterior means and 95% CIs.

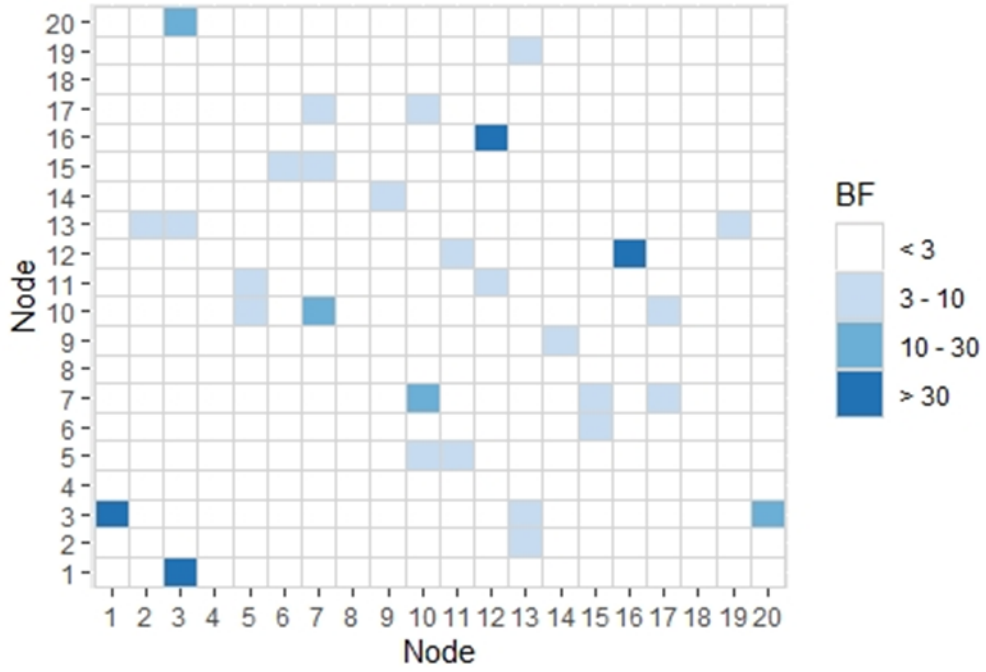
Testing the Global Network Differences and Edge-wise Comparisons

In a next step, we tested for differences between the networks for the two groups. As a test of the global network difference, the predictive *p*-value for the observed JSD rejected the null hypothesis, (*JSD* = 1.40, $p < 0.01$), which means that there were significant differences in the network structure between type I and type II trauma survivors. The sum of the squared error confirmed this global group difference, (*SSE* = 2.58, $p < 0.01$).

In order to better understand differences between the networks, we explored group differences in edge strength and identified 15 edges with BF > 3, favouring the alternative hypothesis that the edge strength differed between the two networks (Figure 2). Table 3 illustrates the selected 12 edges for interpretation, which (a) were recognized in either the network of type I or type II survivors (or both) and (b) showed BF > 3 for the network comparisons; the other three edges appeared neither in the network of type I nor type II survivors. The most prominent difference was found for the edge between the symptoms of intrusions and flashbacks, highlighting the stronger positive association in the group of type II trauma survivors compared to type I survivors. Flashbacks showed a similar pattern of results in the associations with detachment and sleep problems (type II > type I). These group differences were identified even after controlling for the gender differences and education levels (see the supplementary material, Table S6). Additionally, we repeated the analysis without the 32 participants who had not been recruited via treatment centers; results were overall unchanged.

Figure 2

Bayes Factors (BFs) for Edge-wise Group Differences



Note. The empty tiles correspond to a BF that is less than 3 and nodes correspond to PCL items. The Bayesian hypothesis testing provided the relative evidence that group/edges differ (H_1) instead of being equal (H_0).

Table 3

Bayes Factors (BFs) and Posterior Means and Standard Deviations for Edge-wise Group Differences (BF > 3)

Edge (Item number, label)			***BF***	***M***	***SD***
Positive association in type I; Null association in type II					
7-10	*Avoidance of reminders*	*Blame of self or others*	20.11	0.29	0.10
5-10	*Physiological cue reactivity*	*Blame of self or others*	8.48	0.26	0.10
9-14	*Negative beliefs*	*Inability to experience*	6.82	0.25	0.10

Edge (Item number, label)			*BF*	*M*	*SD*
		positive emotions			
7-17	*Avoidance of reminders*	*Hypervigilance*	4.86	0.24	0.10
13-19	*Detachment*	*Difficulty concentrating*	4.63	0.24	0.10
Negative association in type I; Null association in type II					
7-15	*Avoidance of reminders*	*Irritability / anger*	3.67	-0.23	0.10
Null association in type I; Negative association in type II					
12-16	*Self-destructive / reckless behaviour*	*Loss of interest in activities*	31.04	0.31	0.10
Null association in type I; Positive association in type II					
1-3	*Intrusive distressing thoughts or memories*	*Flashbacks*	152.51	-0.33	0.09
10-17	*Blame of self or others*	*Hypervigilance*	8.01	-0.27	0.11
3-13	*Flashbacks*	*Detachment*	5.68	-0.24	0.10
5-11	*Physiological cue reactivity*	*Negative trauma-related emotions*	3.02	-0.22	0.10
Negative association in type I; Positive association in type II					
3-20	*Flashbacks*	*Sleep problems*	26.45	-0.30	0.10

Discussion

Earlier studies investigating PTSD symptom networks have shown large between-study heterogeneity (Isvoranu et al., 2021) suggesting that there may be subgroups of trauma survivors showing systematic differences in symptom network structures. The current study aimed to test whether trauma type is a significant moderator of characteristics in PTSD symptom networks. Based on theoretical and empirical findings on the differences in symptomatology following single-event unexpected traumatic experiences characterized by high acute threat vs. repeated and/or protracted traumatic events, we distinguished between type I and type II trauma to form subgroups within three large samples of treatment-seeking trauma survivors who did not received any interventions at the time of data collection.

Results firstly showed a strong association between all the edges that had been repeatedly documented by the previous network studies (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2021). These robust edges can be interpreted as common features of PTSD symptom networks across different sample populations, including treatment-seeking trauma survivors.

We then tested our hypothesis that there should be significant differences in PTSD symptom networks in survivors of type I vs. type II trauma. In line with our hypothesis, the network comparison test provided strong evidence for a global difference between the networks of the two groups. This global difference endorses the heterogeneity in symptom networks due to the difference in trauma type (Benfer et al., 2018; Macia et al., 2020. There is consistent earlier evidence showing that type II trauma is related to higher symptom severity (Ehring & Quack, 2010), as well as symptom complexity (Briere et al., 2008; Cloitre et al., 2009). The current findings additionally suggest that type I vs. type II trauma also leads to differences in the structure or co-occurrence of PTSD symptoms. If replicated, this could suggest that future studies investigating PTSD symptom networks may benefit from paying

closer attention to trauma type as a moderator, whereby the distinction between type I and type II trauma appears to be a promising starting point. In addition, there may also be implications for the literature focusing on differences in sequelae of type I vs. type II trauma, suggesting that in addition to focusing on the question of whether the different types of trauma lead to different symptoms and/or diagnoses (see: Maercker, Brewin, Bryant, Cloitre, van Ommeren, et al., 2013; Resick et al., 2012), the structure and inter-relationship of symptoms, as well as their potentially causal links, may be important to consider.

As the literature on symptom network models is still at an early stage, it is yet unclear whether the identification of cross-sectional network models also has clinical implications. However, preliminary evidence suggests that pre-treatment cross-sectional symptom networks predict within-subject relationships between symptoms in the sense of change trajectories (Klipstein et al., 2021). Therefore, it appears promising to investigate whether information on differences in symptom network structures between different subgroups of trauma survivors can inform the differential selection of treatment targets.

As symptom networks were found to differ between groups at a global level, we also conducted edge-wise comparisons to explore unique edges for the different trauma groups. The network of type I trauma survivors (but not those with type II trauma) comprised positive associations between the core symptoms of PTSD (e.g., avoidance, cue reactivity) and cognitive and emotional problems (e.g., blame, negative beliefs, lack of positive emotions). On the other hand, the network of type II trauma survivors also showed unique (or stronger) edges compared to those who had experienced type I trauma. For example, flashbacks were closely associated with intrusions, detachment, and sleep problems. Due to the highly exploratory nature of these analyses, these findings should be interpreted with great caution. However, if replicated in future research, the findings might be indicative of a stronger role of dissociative elements in the symptomatology related to type II trauma, with dissociative

flashbacks being closely related to a broad network of symptoms. On the other hand, the findings might suggest a particularly strong relationship between core symptoms of PTSD and cognitive and emotional problems in type I trauma survivors. In addition, the findings are in line with differences in coping behaviour between trauma groups, with a link between avoidance and anger in the type I trauma group, and reckless behaviour and loss of interest in activities in the type II group.

Several limitations are noteworthy. First, the total sample was derived by combining different subsamples that had been recruited at different locations and drawn from slightly different populations. Although heterogeneity to this extent is common in the literature, the generalizability of the findings may be in question. Second, information about participants' history of the psychological and medication treatment could not be collected and reported. Third, the sample size of the current study was around the average of other published network analysis studies on PTSD (Isvoranu et al., 2021). However, replication using larger sample sizes nevertheless appears necessary. Fourth, we were specifically interested in the difference between type I and II trauma; therefore, we did not examine differences between more specific types of events (e.g., physical assaults vs. sexual abuse). Although our results support the view that the rather broad distinction between type I and type II trauma is important to explain some of the heterogeneity found in earlier research, it cannot be ruled out that more specific trauma types may account for additional heterogeneity. Future studies are needed to address this issue.

Despite the limitations, this study provides important evidence for the hypothesis that trauma type is a relevant moderator that may help account for part of the inconsistent findings in PTSD network literature to date. Given that the shape of network depends on what items (symptoms) are included in the analysis, future research should go beyond the item set defined by DSM-5 and additionally include symptoms indicative of more complex PTSD

presentations (e.g., disturbance in emotion regulation, negative self-identity, relationship difficulties). This will provide a more comprehensive picture of the PTSD symptomatology and variants.

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Comparing PTSD Symptom Networks in Type I vs. Type II Trauma Survivors

Supplementary Materials

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Table S1

Items and Clusters of the Post-traumatic Stress Disorder Check List for DSM-5 (PCL-5)

Item	Cluster	Content
1	B (Re-experiencing)	Intrusive distressing thoughts or memories
2	B	Nightmares
3	B	Flashbacks
4	B	Emotional cue reactivity
5	B	Physiological cue reactivity
6	C (Avoidance)	Avoidance of thoughts
7	C	Avoidance of reminders
8	D (Changes in mood and cognition)	Trauma related amnesia
9	D	Negative beliefs
10	D	Blame of self or others
11	D	Negative trauma related emotions
12	D	Loss of interest in activities
13	D	Detachment
14	D	Inability to experience positive emotions
15	E (Hyperarousal)	Irritability / anger
16	E	Self-destructive / reckless behavior
17	E	Hypervigilance
18	E	Exaggerated startle response

Item	Cluster	Content
19	E	Difficulty concentrating
20	E	Sleep problems

Table S2

Posterior Means, SDs, Bayes Factors (BFs) and 95% Credibility Intervals (CI) for the Type I Trauma Network

Edges*	Mean	SD	BF	95% CI	
				LL	UL
1--2	0.23	0.06	> 200.00	0.11	0.35
2--3	0.21	0.06	86.60	0.09	0.33
1--4	0.32	0.06	> 200.00	0.21	0.43
4--5	0.32	0.06	> 200.00	0.21	0.43
4--6	0.26	0.06	> 200.00	0.14	0.37
6--7	0.44	0.06	> 200.00	0.34	0.53
1--10	0.16	0.06	8.21	0.03	0.27
5--10	0.14	0.06	3.41	0.01	0.26
6--10	-0.13	0.06	3.21	-0.25	-0.01
7--10	0.17	0.06	12.24	0.05	0.29
9--10	0.23	0.06	> 200.00	0.12	0.35
1--11	0.18	0.06	14.47	0.05	0.29
4--11	0.22	0.06	172.55	0.12	0.34
9--11	0.19	0.06	36.91	0.07	0.31
10--11	0.22	0.06	174.42	0.10	0.34
10--13	0.16	0.06	9.32	0.04	0.28
12--13	0.40	0.06	> 200.00	0.29	0.50
9--14	0.35	0.06	> 200.00	0.24	0.45
11--14	-0.16	0.06	8.12	-0.28	-0.04

Edges*	Mean	SD	BF	95% CI	
				LL	UL
12--14	0.21	0.06	57.29	0.08	0.33
13--14	0.26	0.06	> 200.00	0.14	0.37
7--15	-0.15	0.06	5.08	-0.26	-0.02
14--15	0.18	0.06	18.62	0.06	0.30
7--17	0.21	0.06	81.18	0.09	0.33
15--17	0.14	0.06	4.77	0.02	0.26
10--18	-0.15	0.06	5.60	-0.27	-0.03
11--18	0.23	0.06	> 200.00	0.11	0.35
17--18	0.49	0.06	> 200.00	0.39	0.58
13--19	0.16	0.06	8.76	0.04	0.28
18--19	0.20	0.06	55.35	0.08	0.32
2--20	0.35	0.06	> 200.00	0.24	0.45
3--20	-0.13	0.06	3.19	-0.25	-0.01
19--20	0.24	0.06	> 200.00	0.12	0.36

Note. Edges with BF > 3 are displayed. The Bayesian hypothesis testing provided the relative evidence that group/edges differ (H_1) than that groups/edges are equal (H_0). Descriptions of the individual item of the PCL-5 can be found in Table S1. LL= Lower limit; UL= Upper limit; *Numbers present PCL items and -- presents relations between those items.

Table S3

Posterior Means, SDs, Bayes Factors (BFs) and 95% Credibility Intervals (CI) for the Type II Trauma Network

Edges*	Post Mean	Post Sd	BF	95% CI	
				LL	UL
1--2	0.28	0.08	152.45	0.13	0.42
1--3	0.43	0.08	> 200.00	0.29	0.55
4--5	0.23	0.08	31.39	0.08	0.38
1--6	0.17	0.08	3.22	0.01	0.32
6--7	0.41	0.08	> 200.00	0.27	0.53
4--10	0.19	0.08	6.70	0.03	0.33
9--10	0.28	0.08	> 200.00	0.14	0.42
4--11	0.22	0.08	18.29	0.07	0.37
5--11	0.23	0.08	22.04	0.08	0.38
7--11	0.19	0.08	6.59	0.03	0.34
10--11	0.27	0.08	116.87	0.12	0.41
5--12	0.21	0.08	12.68	0.06	0.35
8--12	-0.19	0.08	6.55	-0.33	-0.03
3--13	0.26	0.08	68.20	0.11	0.40
12--13	0.44	0.08	> 200.00	0.31	0.56
12--14	0.17	0.08	3.94	0.01	0.33
13--14	0.27	0.08	123.76	0.12	0.40
12--16	-0.24	0.08	40.12	-0.38	-0.09
13--16	0.18	0.08	5.00	0.02	0.32

Edges*	Post Mean	Post Sd	BF	95% CI	
				LL	UL
5--17	0.27	0.08	102.92	0.11	0.41
10--17	0.18	0.08	4.92	0.02	0.32
10--18	-0.19	0.08	5.76	-0.34	-0.03
11--18	0.18	0.08	7.22	0.04	0.35
17--18	0.44	0.08	> 200.00	0.31	0.57
12--19	0.24	0.08	27.57	0.08	0.38
16--19	0.23	0.08	20.92	0.07	0.37
2--20	0.23	0.08	25.10	0.08	0.37
3--20	0.17	0.08	3.73	0.01	0.31
19--20	0.16	0.08	3.13	0.00	0.31

Note. Edges with BF > 3 are displayed. The Bayesian hypothesis testing provided the relative evidence that group/edges differ (H_1) than that groups/edges are equal (H_0). Descriptions of the individual item of the PCL-5 can be found in Table S1. LL= Lower limit; UL= Upper limit. *Numbers present PCL items and -- presents relations between those items.

Table S4

Means, SDs and zero-order correlations of the PCL item– Type I trauma group

Item	n	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	286	2.40	1.30																			
2	286	1.63	1.44	0.63																		
3	286	1.50	1.37	0.57	0.54																	
4	286	2.68	1.30	0.73	0.55	0.54																
5	286	2.14	1.41	0.66	0.58	0.57	0.72															
6	286	2.22	1.39	0.42	0.37	0.37	0.56	0.45														
7	286	1.97	1.45	0.49	0.46	0.42	0.48	0.46	0.60													
8	286	1.17	1.40	0.10	0.15	0.19	0.17	0.10	0.26	0.22												
9	286	1.77	1.48	0.41	0.34	0.45	0.50	0.45	0.40	0.32	0.33											
10	286	1.72	1.42	0.52	0.35	0.43	0.50	0.49	0.31	0.41	0.24	0.53										
11	286	2.31	1.41	0.68	0.49	0.56	0.70	0.64	0.45	0.47	0.26	0.59	0.59									
12	286	1.89	1.43	0.45	0.40	0.41	0.52	0.52	0.40	0.38	0.16	0.48	0.43	0.53								
13	286	1.72	1.45	0.48	0.48	0.46	0.56	0.52	0.41	0.45	0.23	0.52	0.50	0.51	0.73							
14	286	1.57	1.42	0.42	0.43	0.42	0.50	0.49	0.39	0.35	0.22	0.62	0.43	0.44	0.64	0.69						
15	286	1.58	1.41	0.41	0.34	0.42	0.42	0.48	0.34	0.25	0.18	0.43	0.36	0.47	0.43	0.47	0.50					
16	286	0.80	1.11	0.22	0.24	0.32	0.26	0.30	0.19	0.13	0.19	0.39	0.30	0.28	0.36	0.39	0.39	0.36				
17	286	2.05	1.41	0.49	0.45	0.47	0.45	0.54	0.33	0.45	0.11	0.41	0.29	0.52	0.40	0.45	0.37	0.43	0.27			
18	286	2.00	1.40	0.57	0.48	0.53	0.58	0.62	0.39	0.43	0.19	0.54	0.37	0.67	0.53	0.54	0.47	0.45	0.28	0.72		
19	286	2.05	1.41	0.56	0.49	0.49	0.55	0.59	0.36	0.34	0.22	0.54	0.45	0.58	0.60	0.64	0.60	0.49	0.36	0.47	0.64	
20	286	2.25	1.53	0.59	0.64	0.43	0.56	0.56	0.41	0.47	0.20	0.45	0.41	0.57	0.49	0.51	0.46	0.40	0.24	0.48	0.56	0.62

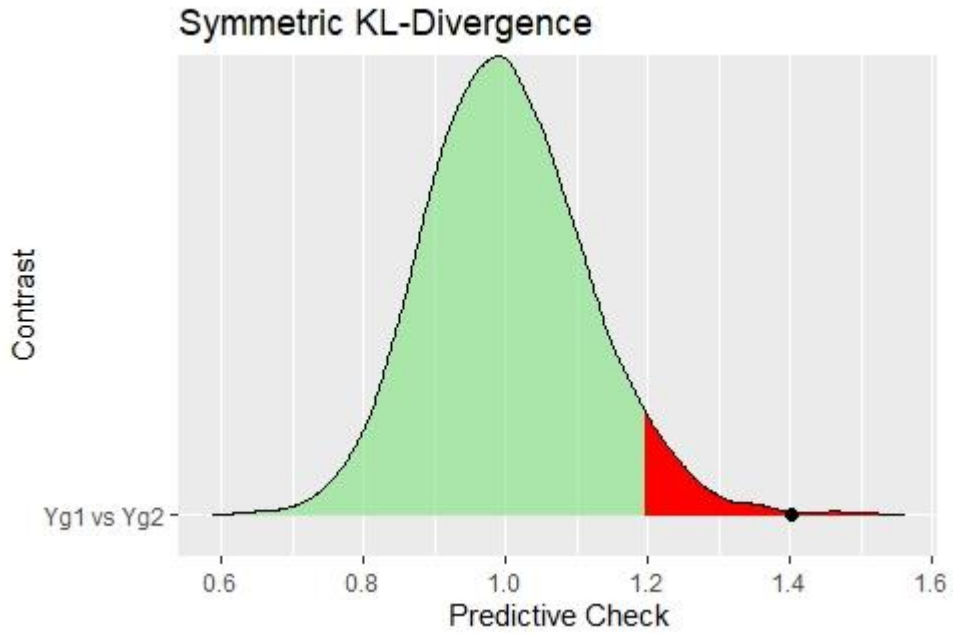
Table S5

Means, SDs and zero-order correlations of the PCL items – Type II trauma group

Item	n	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	187	2.58	1.21																			
2	187	1.88	1.40	0.59																		
3	187	1.84	1.35	0.71	0.53																	
4	187	2.87	1.14	0.63	0.39	0.53																
5	187	2.48	1.28	0.55	0.44	0.50	0.62															
6	187	2.63	1.27	0.53	0.37	0.40	0.54	0.46														
7	187	2.44	1.41	0.43	0.37	0.33	0.50	0.46	0.63													
8	187	1.57	1.39	0.16	0.06	0.19	0.28	0.24	0.28	0.28												
9	187	2.20	1.43	0.44	0.28	0.34	0.48	0.36	0.40	0.42	0.18											
10	187	2.22	1.41	0.47	0.31	0.38	0.51	0.35	0.34	0.30	0.11	0.56										
11	187	2.76	1.25	0.63	0.42	0.50	0.72	0.64	0.52	0.56	0.30	0.57	0.58									
12	187	2.09	1.41	0.39	0.33	0.36	0.31	0.45	0.35	0.40	0.03	0.31	0.33	0.37								
13	187	2.11	1.35	0.40	0.23	0.46	0.37	0.34	0.36	0.41	0.18	0.39	0.34	0.42	0.63							
14	187	1.84	1.38	0.33	0.32	0.35	0.36	0.35	0.33	0.41	0.18	0.45	0.38	0.41	0.56	0.61						
15	187	1.79	1.29	0.3	0.17	0.30	0.35	0.33	0.20	0.29	0.03	0.32	0.27	0.38	0.33	0.39	0.37					
16	187	0.84	1.12	0.27	0.24	0.28	0.32	0.23	0.20	0.22	0.11	0.33	0.20	0.30	0.14	0.35	0.36	0.27				
17	187	2.29	1.32	0.52	0.32	0.47	0.47	0.57	0.40	0.34	0.20	0.34	0.40	0.52	0.41	0.43	0.37	0.36	0.24			
18	187	2.19	1.29	0.52	0.36	0.45	0.53	0.53	0.38	0.35	0.14	0.39	0.33	0.58	0.46	0.45	0.44	0.38	0.33	0.67		
19	187	2.36	1.33	0.41	0.30	0.39	0.48	0.51	0.45	0.41	0.21	0.40	0.29	0.49	0.52	0.44	0.51	0.19	0.39	0.42	0.53	
20	187	2.59	1.36	0.47	0.49	0.49	0.44	0.48	0.37	0.37	0.19	0.45	0.42	0.53	0.44	0.32	0.44	0.27	0.17	0.41	0.47	0.49

Figure S1

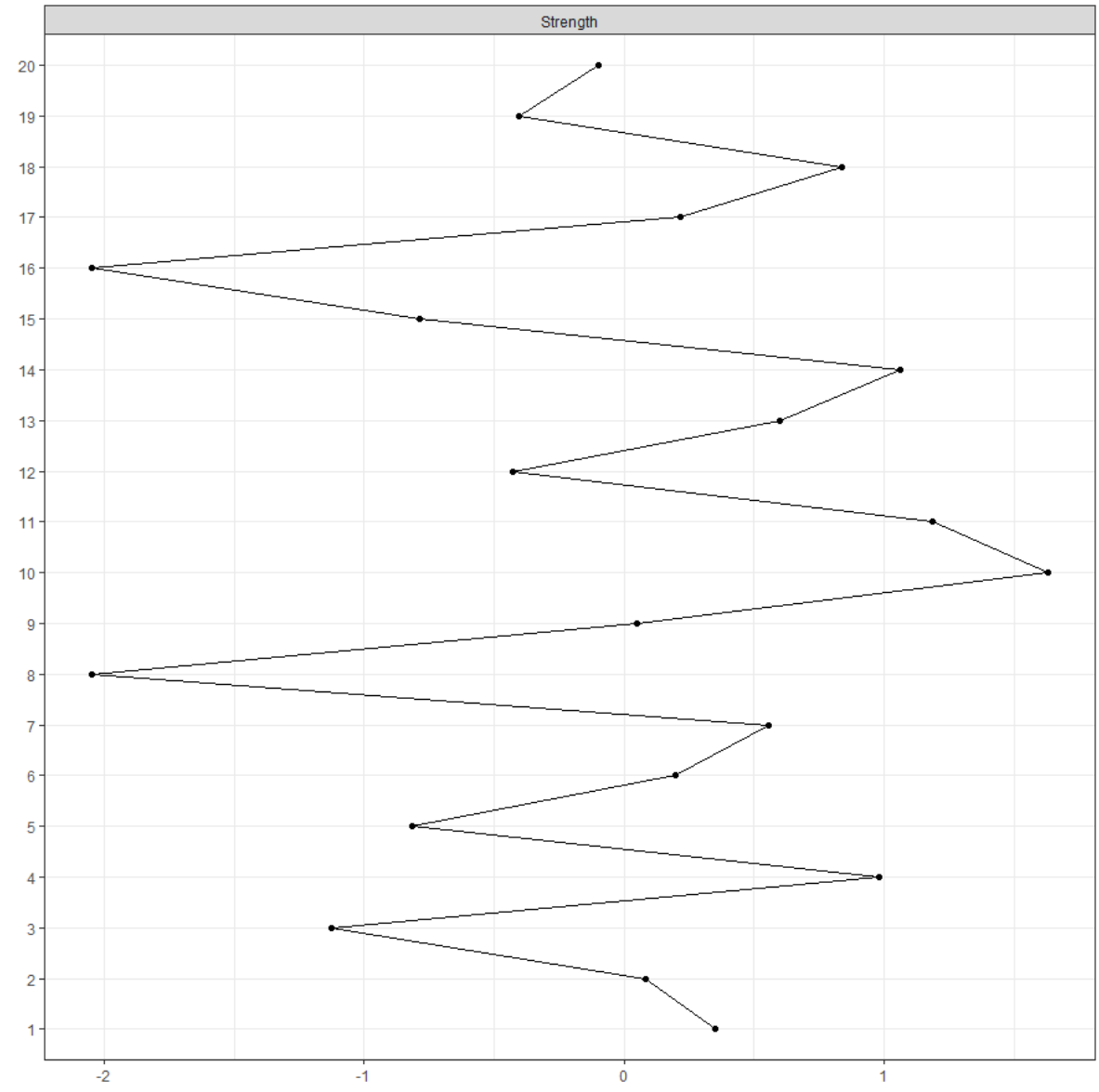
Predictive Distributions for Pairwise Comparisons Between Two Groups (Type I trauma vs Type II trauma survivors)



Note. The observed error is denoted with the black point. The density greater than the observed error is the p value.

Figure S2

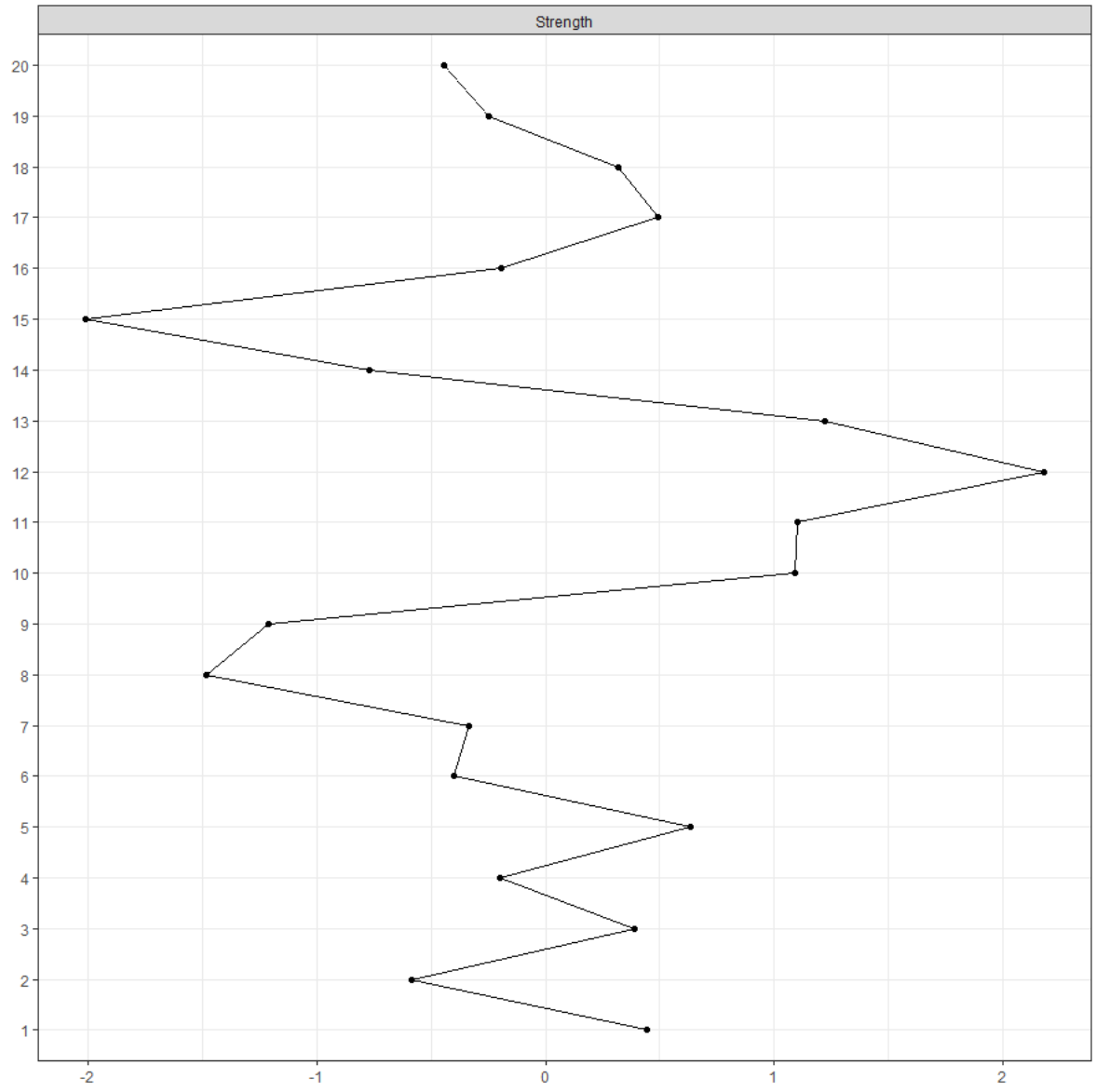
Standardized Node Strength Centrality for the Type I Trauma Network



Note. See Table S1 for a legend of node names

Figure S3

Standardized Node Strength Centrality for the Type II Trauma Network



Note. See Table S1 for a legend of node names

Influences of Gender Differences and Education Levels

We performed regression analyses to clarify whether the effects of trauma types on edge weights could be identified even after controlling for gender differences and education levels. We targeted the edges that showed significant group differences (Table 3), and for each of these edges, we estimated a regression model where a PCL item was predicted by the other items, trauma types, and their interactions after controlling for gender and education levels. Our focus was on the interaction effects, which quantified the differences due to trauma types in the strength of each association between two given items (e.g., the edge weight between Item 7 and 10). In line with previous studies (Birkeland et al., 2017; Gay et al., 2020), we found no evidence that gender differences or education levels influenced the different edge weights – all the expected interaction effects stayed significant even after the additions of the controlling variables (Table S6).

Table S6

Regression Analyses on the Effects of gender differences and education levels

Model for edges:	DV	IV	Estimate	*SE*	*t*	*p*
PCL 7-10, PCL 7-15, PCL 7-17	PCL 7					
		Trauma type*PCL 10	-0.30	0.10	-2.97	< 0.01
		Trauma type*PCL 15	0.26	0.09	2.78	< 0.01
		Trauma type*PCL 17	-0.26	0.11	-2.37	< 0.05
		Gender	-0.08	0.11	-0.71	0.48
		Education 2	0.03	0.16	0.17	0.86
		Education 3	-0.09	0.17	-0.51	0.61
		Education 4	-0.13	0.18	-0.73	0.47
		Education 5	0.14	0.31	0.45	0.65
PCL 5-10	PCL 5					
		Trauma type*10	-0.21	0.08	-2.52	< 0.05
		Gender	0.12	0.07	1.26	0.21
		Education 2	-0.02	0.14	-0.13	0.89
		Education 3	-0.14	0.14	-1.00	0.32
		Education 4	0.04	0.15	0.30	0.77
		Education 5	-0.12	0.26	-0.46	0.64
PCL 9-14	PCL 9					
		Trauma type*14	-0.35	0.11	-3.14	< 0.01
		Gender	0.01	0.11	0.06	0.95
		Education 2	-0.06	0.16	-0.38	0.70
		Education 3	0.05	0.17	0.29	0.77
		Education 4	-0.15	0.18	-0.84	0.40
		Education 5	-0.39	0.32	-1.25	0.21
PCL 13-19	PCL 13					

Model for edges:	DV	IV	Estimate	*SE*	*t*	*p*
		Trauma type*19	-0.27	0.09	-2.89	< 0.01
		Gender	-0.02	0.10	-0.24	0.81
		Education 2	0.12	0.14	0.88	0.38
		Education 3	0.10	0.14	0.68	0.50
		Education 4	0.13	0.15	0.85	0.39
		Education 5	0.12	0.26	0.47	0.64
PCL 12-16	PCL 12					
		Trauma type*16	-0.32	0.10	-3.19	< 0.01
		Gender	0.10	0.10	0.95	0.34
		Education 2	-0.22	0.15	-1.50	0.13
		Education 3	-0.14	0.15	-0.89	0.37
		Education 4	-0.22	0.16	-1.36	0.17
		Education 5	-0.07	0.29	-0.25	0.80
PCL 1-3	PCL 1					
		Trauma type*3	0.27	0.07	3.70	< 0.01
		Gender	0.07	0.08	0.91	0.36
		Education 2	-0.03	0.12	-0.25	0.80
		Education 3	0.06	0.12	0.52	0.61
		Education 4	0.06	0.13	0.44	0.66
		Education 5	-0.07	0.22	-0.33	0.74
PCL 10-17	PCL 10					
		Trauma type*17	0.24	0.11	2.05	< 0.01
		Gender	0.02	0.12	0.21	0.83
		Education 2	0.01	0.17	0.08	0.93
		Education 3	-0.03	0.17	0.18	0.86
		Education 4	-0.09	0.19	-0.50	0.62
		Education 5	-0.16	0.32	-0.51	0.61
PCL 3-13, PCL 3-20	PCL 3					
		Trauma type*13	0.25	0.12	2.09	< 0.05

Model for edges:	DV	IV	Estimate	*SE*	*t*	*p*
		Trauma type*20	0.25	0.10	2.54	< 0.05
		Gender	0.22	0.11	2.01	< 0.05
		Education 2	0.01	0.16	0.09	0.92
		Education 3	0.12	0.14	0.73	0.47
		Education 4	0.09	0.17	0.53	0.59
		Education 5	0.26	0.30	0.86	0.39
PCL 5-11	PCL 5					
		Trauma type*11	0.29	0.12	2.44	< 0.05
		Gender	0.12	0.10	1.26	0.21
		Education 2	-0.02	0.14	-0.13	0.89
		Education 3	-0.14	0.14	-1.00	0.32
		Education 4	0.04	0.15	0.30	0.77
		Education 5	-0.12	0.26	-0.46	0.64

Note. Only the relevant effects were displayed. Each model included, as independent variables, all PCL items (except for the item specified as the dependent variable) and their interactions with trauma types. Gender was dummy-coded with 0 = woman and 1 = man; Education had five levels, which were dummy-coded with *No qualification or only primary school* as the reference; Education 2 = *Middle school or equivalent*; Education 3 = *High school degree*; Education 4 = *University degree*; Education 5 = *Other*.

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Study II

Temporal and Contemporaneous Networks in Posttraumatic Stress Disorder (PTSD)

Stefanovic, M., Takano, K., Wittekind, C. E., Ehring, T., (submitted). Temporal and contemporaneous networks in Posttraumatic Stress Disorder (PTSD).

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M. Stefanovic, T. Ehring, K. Takano and C. Wittekind developed the study concept and design. Data collection was performed by M. Stefanovic and C. Wittekind. K. Takano and M. Stefanovic performed the data analysis and interpretation. M. Stefanovic drafted the manuscript, and K. Takano, T. Ehring, C. Wittekind, provided critical revisions. All authors approved the final version of the manuscript for submission.

Temporal and contemporaneous networks in Posttraumatic Stress Disorder (PTSD)

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We have no conflict of interest to disclose.

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Key points

Question: Which symptoms are most predictive of other symptoms within a day for PTSD patients? Do temporal and contemporaneous networks provide different information?

Findings: Contemporaneous and temporal networks showed different symptom associations, therefore it is important to investigate both. Changes around the within-person centered mean symptom of *hypervigilance* mostly predicted changes around the within-person centered mean of at least one additional symptom from each of the four DSM-5 PTSD symptom clusters.

Meaning: If further research shows that targeting symptoms with the most associations with other symptoms improves treatment efficacy, *hypervigilance* should be considered as a target symptom for PTSD patients.

Abstract

Importance: Contemporaneous and temporal networks of posttraumatic stress disorder (PTSD) symptoms could provide an important insight into the maintenance and dynamic structure of PTSD.

Objective: The current study aimed to investigate the within-day dynamic of PTSD symptoms in PTSD patients, specifically focusing on symptoms that most predict changes in other symptoms.

Design: Data was collected between September 2019 and August 2021. The study included a baseline diagnostic assessment, followed by an assessment using the experience sampling method (ESM) via a smartphone. Participants answered questions related to their PTSD symptoms four time per day for 15 consecutive days.

Setting: Participants were recruited at several in- and outpatient centers in Munich, Germany.

Participants: The sample consisted of 48 treatment-seeking individuals: 44 with PTSD as a primary diagnosis, and 4 patients with subsyndromal PTSD, all of whom had not yet begun trauma-focused treatment. Exclusion criteria were lack of memory of the trauma, a current/lifetime diagnosis of schizophrenia or borderline personality disorder, substance use disorder within the past month, and acute suicidality.

Main Outcome(s) and Measure(s): The ESM assessment included the 20 items from the PTSD Checklist for DSM-5, five items from the International Trauma Questionnaire (ITQ) assessing disturbances in relationships and functional impairment, and two items from the Clinician-Administered PTSD Scale for DSM-5 assessing symptoms of depersonalization and derealization.

Results: Contemporaneous and temporal networks showed different symptom associations. Temporal networks showed that changes in *hypervigilance* predicted changes in the greatest number of symptoms at the next time point. Furthermore, *hypervigilance* showed temporal connections with at least one additional symptom from each of the DSM-5 PTSD symptom clusters.

Conclusions and Relevance: Hypervigilance in PTSD patients prospectively predicts changes in many other symptoms. This may be important to consider in treatment planning.

Keywords: posttraumatic stress disorder, ESM, network analysis, multilevel VAR

Temporal and contemporaneous networks in Posttraumatic Stress Disorder (PTSD)

Two out of three people in a general population worldwide experience a traumatic event during their lifetime (Kessler et al., 2017). A substantial subgroup of trauma-exposed individuals develop PTSD (Atwoli et al., 2015), which is related to high disability and considerable socioeconomic burden (Warth et al., 2020). However, the definition of PTSD is rather complex. For example, the Diagnostic and Statistical Manual of Mental Disorders (DSM-5: American Psychiatric Association, 2013) conceptualizes PTSD as comprising 20 specific symptoms, which are divided over four symptom clusters to which a complex algorithm is applied. As a consequence, PTSD is far from being a homogenous disorder; instead, a very large number of different symptom combinations are possible that ultimately lead to a PTSD diagnosis (Galatzer-Levy & Bryant, 2013). In addition, it appears likely that these symptoms are not independent, but rather show a number of uni- or bi-directional relationships.

To better understand the inter-relationship of PTSD symptoms, researchers have used the network approach, which helps to infer the co-occurrence pattern between symptoms (Borsboom et al., 2018; Epskamp et al., 2016; Hofmann et al., 2016). Most earlier studies have focused on cross-sectional networks that represent symptom co-occurrence across a group of individuals at one point of assessment (e.g., patients who experience hypervigilance are easily startled; those who often experience nightmares tend to suffer from intrusive thoughts) (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2021).

Although cross-sectional networks are relevant as they may provide information on the underlying causal structure of PTSD symptoms (Hofmann et al., 2016), one crucial limitation of this approach is that it does not tap into the dynamic interplay between symptoms (Birkeland et al., 2020; Isvoranu et al., 2021). To address this limitation,

researchers have recently started to use intensive longitudinal assessments to capture day-to-day (or even shorter, e.g., half-a-day) changes in symptoms and to estimate the temporal, directed associations between symptoms within an individual (Epskamp et al., 2018). Following the seminal work by Greene and colleagues on Israeli civilians exposed to rocket fire (Greene et al., 2018), temporal networks of PTSD symptoms have been estimated for traumatized individuals in an acute post-trauma phase (Price et al., 2020), for PTSD patients undergoing exposure treatment (Hoffart et al., 2019), and for a mixed group of individuals meeting the criteria for PTSD (Reeves & Fisher, 2020). In these temporal networks, central symptoms that are most predictive of other symptoms at a later time point (i.e., high out-strength) were identified, namely *exaggarated startle response* (Greene et al., 2018), *hypervigilance* and *physiological reactivation* (Hoffart et al., 2019), *low interest* (Price et al., 2020), and *negative trauma-related emotions* (Reeves & Fisher, 2020). Despite inconsistencies between specific findings, as a whole these studies provide converging evidence that different shapes emerge for temporal (within-person) networks than those that emerge for cross-sectional (between-person) networks (Birkeland et al., 2020; Isvoranu et al., 2021). It has therefore been suggested that studying temporal dynamics in symptom networks should have a high priority in this field of research.

The primary focus of the current study was to examine the dynamic interplay between symptoms among PTSD patients. We asked participants to report their symptoms via a smartphone app four times per day for 15 consecutive days (i.e., experience sampling method; ESM). Although most earlier studies have used less frequent (e.g., daily) assessments, we decided to use a more intensive assessment approach since acute changes in symptoms can take place within hours, particularly in vulnerable individuals (Schuler et al., 2021), and as PTSD symptoms can easily be triggered by situational and environmental factors (e.g., loud

noises; Naragon-Gainey et al., 2012). Therefore, it seemed crucial to obtain a time series of symptoms with high temporal resolution and high ecological validity. In addition to the DSM-5 symptom criteria for PTSD, additional aspects related to PTSD (e.g., disturbances in relationships, functional impairment, and depersonalization and derealization) were included to better understand the role of these symptoms in dynamic network structures of PTSD symptoms.

Using this data, we estimated two types of networks: *contemporaneous* networks representing the partial correlations between symptoms recorded at the same time of measurement, and *temporal* networks illustrating how symptoms influence each other at the subsequent measurement (Epskamp et al., 2018).

Method

Participants

Participants were recruited between September 2019 and August 2021 via advertisements and flyers distributed in different in-patient and outpatient treatment centers in Munich, Germany, as well as through flyers distributed at various trauma centers, and through online advertisements. The inclusion criteria for participants were: age between 18 to 60 years; fluency in German; and exposure to a traumatic event based on DSM-5 criteria (American Psychiatric Association, 2013) with PTSD (or sub-syndromal PTSD that did not meet the full DSM-5 criteria, which was the case of $n = 4$ participants[3]) as a primary diagnosis. Additionally, the participants had to be attending a PTSD treatment center but could not yet have started receiving trauma-focused treatment, as we wanted to avoid any ongoing treatment impacting the symptom networks. Participants were not eligible to participate in the current study if they had no memory of the trauma, had a current or lifetime diagnosis of

[3] These 4 participants attended one of the specialized treatment centers for their PTSD symptomatology but did not meet full DSM-5 criteria in the structured interviews.

schizophrenia or borderline personality disorder, had substance use disorder within the past month, or acute suicidality. The final sample comprised 48 participants (for detailed sample characteristics, see Table 1; the flow of participants is provided in Figure S1 in the supplementary material).

Table 1

Sample Characteristics (N = 48)

Characteristics	*Mean (SD) or N (%)*
Age (years, M, SD)	38.89 (13.51)
Gender (n, %)	
Women	35 (72.92%)
Men	13 (27.08%)
Education (n)[a]	
Middle school or equivalent	21 (43.75%)
High school degree	13 (27.08%)
University degree	12 (25%)
Type of traumatic event experienced (n) [a]	
Accident	3 (6.25%)
Physical assault	11 (22.92%)
Sexual assault	28 (58.33%)
Life-threatening illness or injury	2 (4.17%)
Any other very stressful event or experience	2 (4.17%)
Comorbidity disorders (n)	

Characteristics	*Mean (SD) or N (%)*
Depression	12 (25%)
Obsessive compulsive disorder	4 (8.3%)
Substance use disorder	4 (8.3%)
Anxiety disorder	4 (8.3%)
ADHD[b]	1 (2.08%)
Treatment setting (n)[c]	
Inpatients	15 (31.25%)
Outpatients	26 (54.17%)
Not in treatment	7 (14.58%)

[a]data of 2 participants was missing; [b]ADHD= Attention Deficit Hyperactivity Disorder; [c] Participants were in an assessment phase and had not yet begun any trauma focused treatment

Measures

Baseline Measures

The Structured Clinical Interview for DSM-5 (SCID-5-CV)[4] (Beesdo-Baum, K., Zaudig, M., & Wittchen, H.-U., 2019) or the Clinical Administered PTSD Scale for DSM-5 (CAPS-5) (Schnyder, 2013; Weathers et al., 2018) were used to verify a diagnosis of PTSD. Comorbid disorders were assessed with the SCID-5-CV for all participants.

The PTSD Checklist for DSM-5 (PCL-5) (Krüger-Gottschalk et al., 2017; Weathers, Litz, et al., 2013) is a 20-item DSM-5-based self-report measure for PTSD that was used to assess PTSD symptom severity in the past month.

[4] When data collection for this study started, SCID-5-CV was not yet available in all outpatient centers. With the intention of simplifying the process for the patients, if a diagnostic was already provided with the SCID-4 and CAPS, we did not repeat the diagnostic part, as all patients were diagnosed according to DSM-5 criteria.

The Life Events Checklist (LEC-5) (Weathers, Blake, et al., 2013) was used as a self-report measure to assess trauma exposure to 16 specific traumatic events plus one additional open item.

ESM Items

At each ESM assessment occasion, participants rated 27 items, including the 20 items from the PCL-5 assessing all DSM-5 symptoms of PTSD, and 2 items adapted from the CAPS-5 to assess depersonalization and derealization symptoms. In addition, 5 items from the International Trauma Questionnaire (ITQ: Cloitre et al., 2018) assessing disturbances in interpersonal relationships (2 items; feeling distant or cut off from other people; difficulties staying emotionally close to other people), and functional impairment (3 items; impairments of relationships and social life; work; and in other areas of life) were used. Participants reported the intensity of their symptoms on a 5-point scale (0=*absent* to 4=*extremely*). The wordings for all items were modified to assess PTSD symptoms experienced since the previous ESM assessment occasion, except for the first occasion of each day, which targeted symptoms since waking up in the morning. The two sleep-related items from the PCL-5 were used only in the first assessment of each day.

Procedure

Participants were first contacted via phone to assess eligibility and were then invited for the first face-to-face assessment where they received information about the study and provided informed consent. We then conducted the clinical interviews to verify PTSD diagnosis and other comorbid disorders. Afterwards, participants completed the sociodemographic and symptom questionnaires, received instructions about the procedure for the smartphone assessments, and installed the ESM app on their own smartphone or on a smartphone provided by the research team. During the course of assessment (15 consecutive

days), notifications were sent 4 times per day, scheduled in semi-randomized timing, each separated by approximately four hours. In response to each notification, participants were asked to rate their current levels of PTSD symptoms. Depending on their sleep habits, participants could choose the start time of each day at around 8:30, 9:30, or 10:30 AM. If participants did not respond to a notification, they received a reminder 20 minutes later. If the reminder was also missed, participants were instructed to respond to the next notification. After completing all smartphone assessments, participants were invited for another appointment and received 35€ as a fee for participating. This study was approved by the ethics committee of the Department of Psychology, LMU Munich.

Statistical analysis

We estimated two types of networks (i.e., contemporaneous and temporal) on ESM-assessed PTSD symptoms. Contemporaneous networks represent the relationship between given symptoms within the same assessment occasion, whereas temporal networks represent prospective associations between symptoms (Epskamp et al., 2018). We used a two-step estimation approach (Bringmann et al., 2013; Epskamp et al., 2019). First, we estimated the temporal network using multilevel, lag-1 vector autoregressive (VAR) models, in which each symptom was predicted by itself, and other symptoms were assessed at the previous occasion. Second, the contemporaneous network was specified as another set of multilevel VAR models on the residuals of the temporal network. It is recommended to exclude the potential influences of the symptoms observed at the previous moment and thus to focus solely on the within-occasion effects[5]. The estimated fixed effects were mapped onto each network as edges connecting PTSD symptoms represented as nodes. Participants' responses made in the

[5] As a VAR model assumes the stationarity for each time series, we confirmed that there was no significant time trend on the PCL, ITQ, or CAPS scores.

first assessment occasion of each day (and thus the two sleep items) were excluded from the network analyses because a VAR model assumes a constant interval between proximate time points. We assumed the orthogonal covariance structure for the random effects as we encountered convergence problems with the assumption of the correlated structure (Epskamp et al., 2019). To describe the network characteristics, centrality indices were computed for each type of network. For the contemporaneous network, standardized strength centrality was estimated for each node, which is given by the sum of the edges connected with the node. For the temporal network, we defined in- and out-strength for each node in order to identify the symptoms that were most predicted by other symptoms (in-strength) and symptoms that mostly predicted other symptoms (out-strength). These network analyses were performed using the R package, mlVAR (Epskamp et al., 2019).

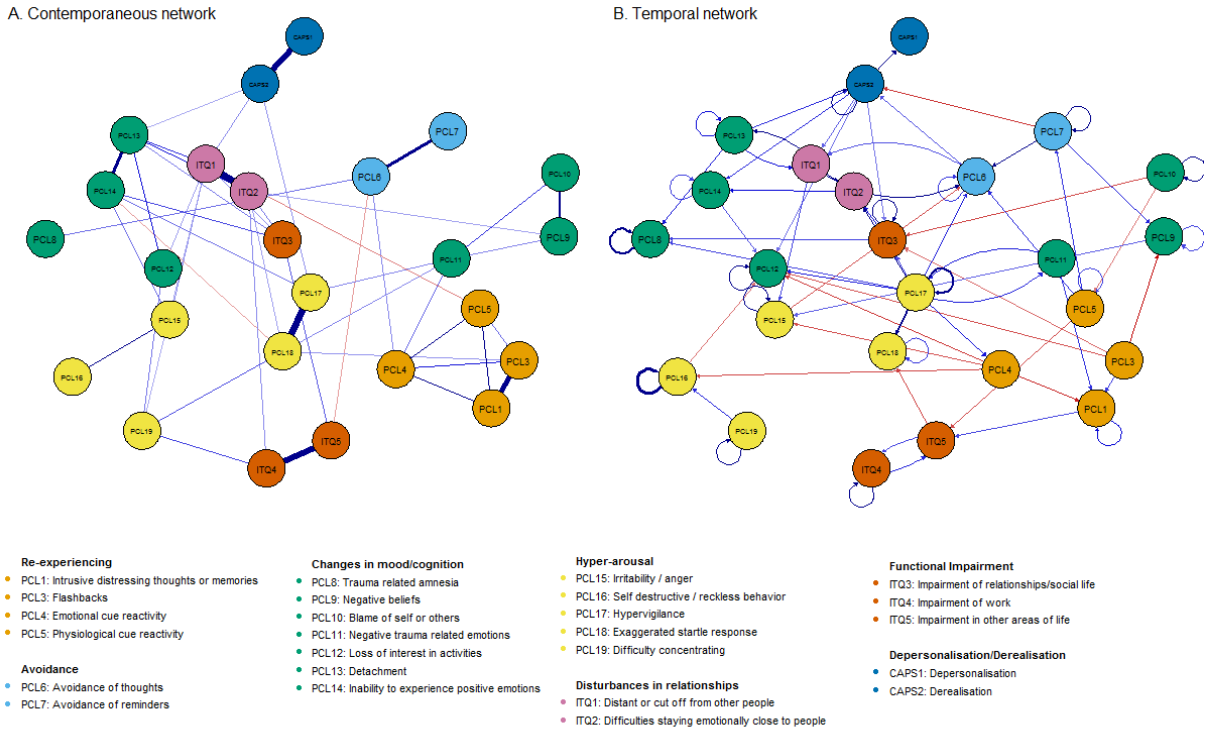
Results

Sample Characteristics and Compliance

The mean number of valid ESM responses per person was 41.47 (*SD* = 14.64; Range = 5 – 60) out of a total of 60 notifications. As we did not find a systematic pattern in the missingness (e.g., null correlation between the PCL score and compliance), all participants were included in the network analyses. Additionally, we confirmed that results were unchanged overall if we excluded participants with low compliance (e.g., 18 or fewer valid responses).

Figure 1

Estimated Symptom Networks – Contemporaneous (Panel A) and Temporal (Panel B)



Note. Red edges represent negative associations whereas blue edges represent positive associations between symptoms. A self-directed edge indicates an auto-regressive effect of a symptom on the same symptom at the next time point.

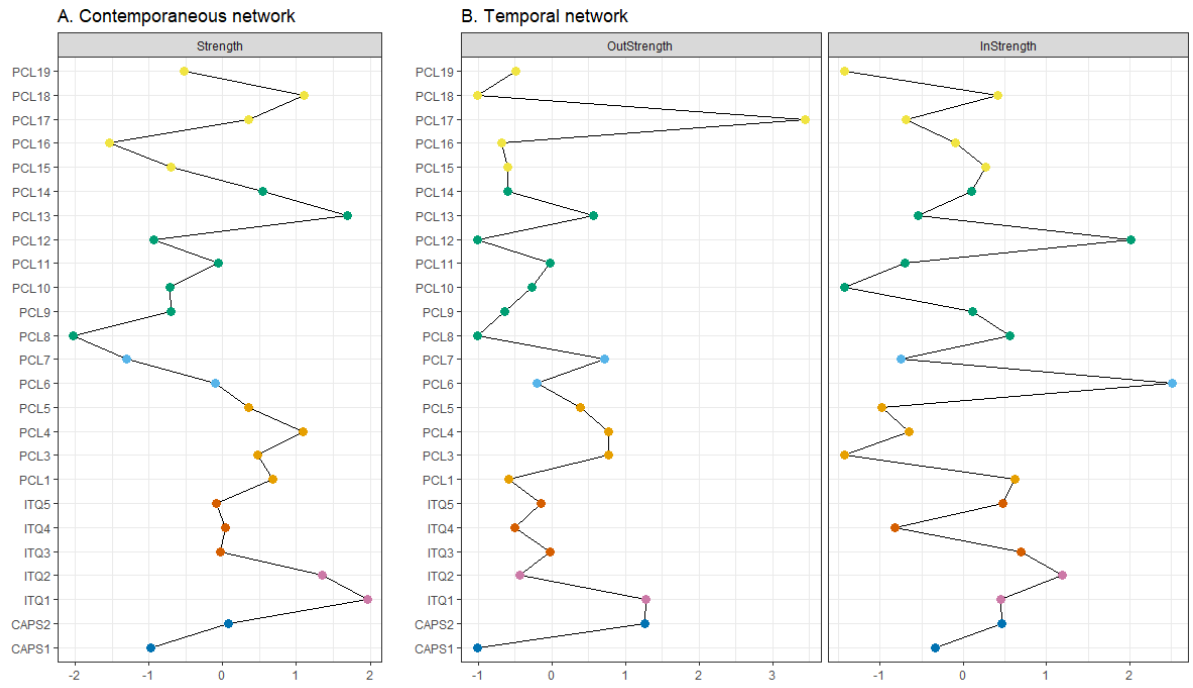
Contemporaneous Network

Figure 1 (Panel A) shows the estimated contemporaneous network, while Figure 2 (Panel A) illustrates standardized node strength centrality for the contemporaneous network. Information about partial correlation for the contemporaneous network is provided in the Supplementary Material (Table S1). First, the strongest edges were found between the

following nodes: *feeling distant or cut off from other people* and *difficulties staying emotionally close to people* (partial correlation edge weight = .34); *hypervigilance* and *exaggerated startle response* (.34); *impairment of work* and *impairment in other areas of life* (.33); and *depersonalization* and *derealization* (.32). Second, items belonging to the symptom cluster "changes in mood and cognition" fell into two sub-groups: one sub-group was closely related to the two nodes in the category "disturbances in relationships", and the other sub-group shows associations with the cluster "re-experiencing". Third, the node with the highest strength centrality was *feeling distant or cut off from other people.* On the other hand, *amnesia* showed the lowest strength.

Figure 2

Standardized Node Strength Centrality for the Contemporaneous Network (Panel A) and Out- and in- Strength Centrality for the Temporal Network (Panel B)



Note. See Figure 1 for the symptom labels and clusters (colored)

Temporal Network

Figure 1 (Panel B) shows the temporal network, and Figure 2 (Panel B) illustrates out- and in-strength centrality for the temporal network. Detailed information about temporal fixed effects and standard errors for temporal network fixed effects is provided in the supplementary material (Table S2, Table S3). First, the estimated temporal network showed significant auto-regressive effects for most of the symptoms, which suggests that PTSD symptoms were generally inert and only changed gradually over time. Second, compared with the contemporaneous network, a larger number of negative edges emerged in the temporal network. Third, the highest out-strength centrality was found for *hypervigilance*, which was followed by *derealization* and *feeling distant from other people*. These results imply that, for example, the more hypervigilant a person is at one moment, the higher the levels of other symptoms they experience at the next moment. The nodes with the highest in-strength centrality (i.e., the nodes that are the most predicted by other nodes) were *avoidance of thoughts* and *loss of interest in activities*. The temporal network comprised more negative correlations than the contemporaneous network, and the nodes with the most negative correlations in the temporal network were *emotional cue reactivity* and *flashbacks*, respectively.

Discussion

We investigated dynamic PTSD symptom networks in patients attending specialized treatment centers – but before they had received trauma-focused treatment – by estimating contemporaneous and temporal networks. Analyzing the centrality and association between nodes, there was a markable difference between contemporaneous and temporal networks. The temporal network comprised more negative correlations, specifically increase of *emotional cue reactivity*, led to decrease of *intrusive distressing thoughts or memories*, *self-destructive behavior*, *irritability/anger* and *loss of interest in activities*; increase of *flashbacks* led to decrease of *negative beliefs*, *impairment of relationships* and *loss of interest in activities* at the next time point and vice versa. In the contemporaneous network, symptoms showed a stronger synchronization with only a few negative correlations. Also, some edges were present in the contemporaneous network but not in the temporal network and vice versa, emphasizing the need to analyze both networks separately (Epskamp et al., 2018; Greene et al., 2018).

Some findings from previous studies were replicated. First, the items included in the DSM-5 cluster *changes in mood and cognition* fell into two sub-groups, consistent with the study by Greene et al. (2018) and the dimensional structure of PTSD according to DSM-5 (Armour et al., 2015; Pietrzak et al., 2015). Second, in the contemporaneous network, amnesia was found to be the node with the lowest strength, which has been found repeatedly in earlier cross-sectional networks studies (Birkeland et al., 2020; Isvoranu et al., 2021). However, the finding is not in line with two previous PTSD dynamic network studies (Greene et al., 2018; Reeves & Fisher, 2020).

The changes around the within-person centered mean of *hypervigilance* predicted changes in most other symptoms at the next measurement. It has been argued that these

temporal associations identified in a network analysis may be interpreted as indicators of the Granger causality (Epskamp et al., 2018), a term originating from the economic literature that signifies a potential indicator of causality (Granger, 1969). From a clinical perspective, it appears relevant to test whether targeting symptoms with the highest out-strength is related to higher treatment efficacy than targeting other symptoms, which may ultimately lead to defining symptoms of primary and secondary focus (Hoffart et al., 2019; Wichers et al., 2017). Hyperarousal occurs when a person suddenly goes into a state of increased alertness: even though there is no real danger, the person behave as if there is. Identifying hypervigilance as the symptom with the highest out-strength is in line with the key components of prolonged exposure treatment where in-vivo exposure can be seen as directly targeting this symptom (Foa et al., 2007). In an earlier study conducted during exposure therapy with PTSD patients, *hypervigilance* and *physiological reactivity* were indeed found to be symptoms with the highest out-strengths (Hoffart et al., 2019).

In the current study, *feeling distant or cut off from other people* was additionally found to have many direct connections to other nodes in the contemporaneous network, and to have effects on many other nodes in the temporal network; thus, this variable potentially also plays an important role in PTSD maintenance.

Several limitations of the study and directions for future studies are noteworthy. First, although our sample size is within the range of earlier studies investigating temporal PTSD networks based on intensive ESM sampling in a patient population (e.g., Hoffart et al., 2019; Reeves & Fisher, 2020), our findings nevertheless need to be replicated using larger samples. Second, not all the participants in our sample satisfied the usually recommended criterion of 20 observation per person (Ramseyer et al., 2014). Third, network models depend on the symptoms included in the network. We based our model on PTSD symptoms according to

DSM-5 and additionally included symptoms related to the dissociation, interpersonal problems, and functional impairment according to ICD-11 as these cover a wide spectrum of PTSD characteristics. Nevertheless, other variables may be important to consider, such as frequent comorbid symptoms (e.g., depressive symptoms; substance use) and information on external variables (e.g., environmental risk factors (Borsboom, 2017; Isvoranu, 2021)). Fourth, we tested a heterogenous sample of trauma survivors with PTSD. However, there is a first indication from a cross-sectional network study that trauma type may be a moderator (Stefanovic et al., 2022). Therefore, future studies should include trauma type as a moderator in temporal network studies that requires larger sample size.

To conclude, despite the limitations, our study provided information about the within-day dynamics of PTSD symptoms in a clinical sample. Results show that contemporaneous and temporal networks differ and that it is important to estimate both. Some findings from earlier research are replicated, but heterogeneity across studies remains. Future studies should include potential moderators in the model (e.g., trauma type), and estimate idiographic networks following the work from Reeves and Fisher (2020) as a possible starting point for using temporal networks as a basis for personalized interventions.

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Temporal and contemporaneous networks in Posttraumatic Stress Disorder (PTSD)

Supplementary Material

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Figure S1

Total Number of Screened and Included Participant

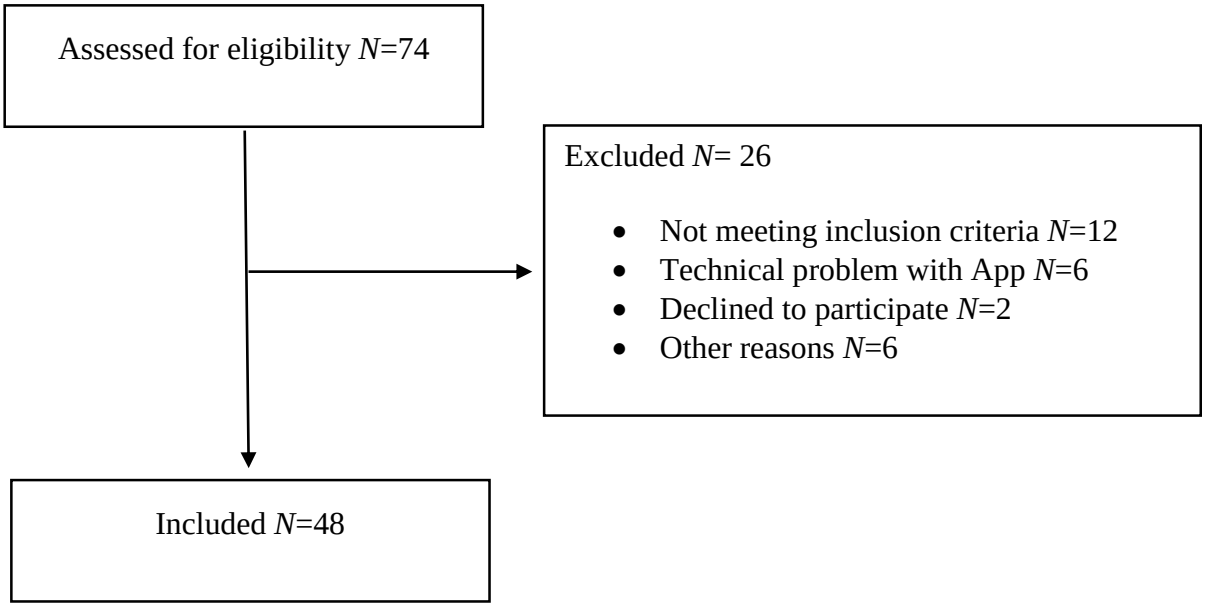

Table S1

Partial correlation matrix for contemporaneous network

	PCL1	PCL3	PCL4	PCL5	PCL6	PCL7	PCL8	PCL9	PCL10	PCL11	PCL12	PCL13	PCL14	PCL15	PCL16	PCL17	PCL18	PCL19	ITQ1	ITQ2	ITQ3	ITQ4	ITQ5	CAPS1	CAPS2
PCL1		0.28*	0.19*	0.20*	0.03	0	0.02	0.03	0.06	-0.01	0.01	0.01	0.03	0.04	0.02	0	0.03	0.02	-0.01	-0.02	0.03	-0.01	0	0.04	0.02
PCL3			0.17*	0.11*	0	0.06	0.04	0.04	-0.06	0.06	0.06	-0.03	0.05	-0.04	0.01	-0.03	0.07 *	0.02	0	-0.02	-0.04	0.03	0.02	-0.03	0.05
PCL4				0.21*	0.08*	0	0.02	0.03	0.06	0.11 *	0	-0.01	0.02	0.01	0.05	0	0.04	-0.05	0.06	0.03	0	-0.03	0.02	-0.01	0.06
PCL5					0.06	0.04	0.04	0.04	0.02	0.02	-0.01	0.04	0.01	0.04	0.01	0.04	-0.03	0.03	-0.09*	0.05	0.03	0.03	0.03	0.01	0.04
PCL6						0.26*	0.10*	0	0.03	0	0.04	-0.01	0.04	0.05	0	0	-0.03	0.02	-0.02	-0.01	0.01	0.06	-0.07*	0.05	-0.01
PCL7							0.08	0.04	0.04	-0.01	0.08	0.02	-0.03	-0.05	0.05	0.07	0.05	0	0.03	0	0.04	0.01	0.01	0	-0.04
PCL8								-0.01	0.01	0.06	0.04	0.03	0.02	-0.01	0.03	-0.04	0.06	0	-0.03	-0.01	0.01	0	-0.04	0.03	-0.01
PCL9									0.23 *	0.09 *	0.04	0.01	0.04	0.05	0.03	-0.01	0.01	0	0.01	0.06*	0.05	-0.02	-0.03	0.04	0.03
PCL10										0.15 *	0.04	0.03	0.01	0.05	-0.03	0.02	0.03	-0.02	0.02	-0.01	-0.03	-0.02	0.05	0	-0.05
PCL11											0.08	-0.02	0.01	0.03	-0.01	0.09 *	0.09 *	0.05	-0.02	0.02	-0.04	0.04	0.06	0.05	0.03
PCL12												0.17 *	0.05	0.04	0.06	0.06	-0.06	0.10 *	0.07*	0	0.03	-0.02	0.02	0.04	-0.05
PCL13													0.24 *	0.03	0.04	-0.03	0.05	-0.03	0.15*	0.17*	0.10*	0.04	0.03	0.01	0.06 *
PCL14														0.10 *	-0.02	0.10 *	-0.07 *	0.02	0.07	0	0.13*	-0.01	0	0.02	0
PCL15															0.21 *	0.01	0.03	0.06	0.07*	0.04	-0.03	0	0.03	0.04	-0.03
PCL16																0.04	0.01	-0.01	-0.06	0	0.07	0.01	0	-0.06	0.01
PCL17																	0.34 *	0.02	-0.01	0.04	0.03	0.02	0.05	-0.02	0.08 *
PCL18																		0.13 *	0	0.07*	0.01	0.03	-0.04	0.04	0.02
PCL19																			0.06*	0.05	-0.05	0.13*	0.07	0.05	0.07
ITQ1																				0.34*	0.08*	0.03	-0.01	-0.01	0.08 *
ITQ2																					0.10*	0.08*	0.03	-0.01	0.01
ITQ3																						0.09	0.12*	0.03	-0.01
ITQ4																							0.33*	-0.02	0.01

	PCL1	PCL3	PCL4	PCL5	PCL6	PCL7	PCL8	PCL9	PCL10	PCL11	PCL12	PCL13	PCL14	PCL15	PCL16	PCL17	PCL18	PCL19	ITQ1	ITQ2	ITQ3	ITQ4	ITQ5	CAPS1	CAPS2
ITQ5																								0.05	0.03
CAPS1																									0.32 *
CAPS2																									

Note. * illustrates significant edges

Table S2

Temporal fixed effects lag-1

	PCL1	PCL3	PCL4	PCL5	PCL6	PCL7	PCL8	PCL9	PCL10	PCL11	PCL12	PCL13	PCL14	PCL15	PCL16	PCL17	PCL18	PCL19	ITQ1	ITQ2	ITQ3	ITQ4	ITQ5	CAPS1	CAPS2
PCL1	0.12*	0.06	0.04	0.01	0.04	-0.03	0.00	0.04	0.04	0.03	0.07	0.03	0.00	0.06	-0.01	0.03	-0.01	0.00	0.03	0.03	0.04	0.02	0.09*	-0.02	0.06
PCL3	0.10*	0.10	0.00	0.00	-0.08	-0.01	0.02	-0.12*	-0.04	-0.01	-0.08*	-0.06	-0.06	0.05	0.03	-0.01	0.07	-0.05	-0.03	0.00	-0.07*	-0.07	-0.06	-0.02	-0.07
PCL4	-0.10*	0.08	0.00	-0.07	-0.03	-0.02	-0.06	-0.01	-0.02	-0.03	-0.09*	0.00	-0.05	-0.08*	-0.09*	0.01	0.02	0.04	0.03	0.00	0.05	-0.01	0.06	0.04	0.03
PCL5	-0.05	0.02	0.06	0.09*	0.10*	0.10*	0.04	0.03	0.05	0.00	0.03	0.01	0.06	0.00	0.04	-0.04	0.00	-0.05	-0.04	-0.05	-0.01	-0.01	-0.09*	-0.03	-0.05
PCL6	0.07	0.05	0.05	0.05	0.10*	0.07	0.05	-0.04	-0.08	0.01	0.01	0.04	0.03	-0.05	0.02	0.01	-0.01	-0.03	0.08*	0.02	0.04	0.01	0.00	0.06	0.08*
PCL7	0.00	-0.04	0.02	0.01	0.16*	0.15*	0.01	0.10*	-0.07	-0.05	0.04	-0.04	-0.04	-0.05	-0.04	0.01	0.01	0.01	-0.03	-0.03	-0.06	0.04	0.04	-0.05	-0.09*
PCL8	-0.02	-0.01	-0.04	-0.02	-0.01	-0.04	0.17*	-0.01	-0.02	-0.05	-0.03	-0.02	-0.06	0.05	0.03	0.01	0.05	-0.02	-0.04	0.00	-0.04	0.02	-0.03	0.04	-0.03
PCL9	-0.02	-0.01	0.01	0.04	-0.03	0.00	0.01	0.09*	-0.02	0.04	0.00	0.00	-0.05	0.08*	0.03	0.00	0.02	0.03	-0.01	0.02	0.08	-0.02	0.03	0.07	0.05
PCL10	-0.04	-0.04	-0.06	-0.06*	0.04	-0.07	0.01	0.02	0.14*	-0.02	-0.01	-0.06	0.00	-0.04	0.03	-0.02	-0.04	0.03	-0.03	-0.05	-0.09*	-0.02	-0.04	-0.05	-0.04
PCL11	0.10*	0.04	0.10	0.03	-0.02	0.02	0.01	0.06	0.00	0.07	0.02	0.05	0.08	0.08	0.03	0.11*	0.00	0.03	-0.01	-0.03	-0.03	0.06	0.05	0.11	0.07
PCL12	0.02	0.02	0.06	0.00	0.01	0.02	0.00	0.03	0.04	0.05	0.16*	0.01	0.07	-0.04	-0.01	0.01	0.02	0.05	0.03	0.04	0.03	0.01	0.03	0.02	0.02
PCL13	-0.04	0.00	-0.03	-0.03	0.00	0.00	0.11*	0.03	0.03	0.00	-0.01	0.11*	0.08	0.03	0.07	0.00	0.06	0.01	0.12*	0.06	0.04	0.06	0.07	0.05	0.10*
PCL14	0.06	0.06	0.05	0.02	0.02	-0.02	0.01	0.04	0.05	0.05	0.08*	0.04	0.09*	0.03	-0.01	-0.01	-0.03	0.04	0.05	-0.01	0.01	0.02	-0.04	0.06	0.03
PCL15	0.01	0.03	0.03	0.02	-0.08*	-0.04	-0.05	0.06	0.06	0.05	0.01	-0.01	0.02	0.14*	0.01	0.03	-0.02	0.00	-0.05	0.01	0.00	-0.01	0.00	-0.04	-0.04
PCL16	0.02	0.06	-0.03	0.01	0.04	0.02	0.00	-0.04	0.01	-0.02	-0.07*	0.00	-0.05	0.04	0.21*	-0.02	0.04	0.01	0.03	-0.04	0.00	0.01	0.04	-0.04	-0.01
PCL17	0.08	0.06	0.11*	0.09	0.11*	0.00	0.09*	0.07	0.03	0.10*	0.11*	0.00	0.07	0.01	-0.04	0.17*	0.18*	0.07	0.06	0.14*	0.09*	0.00	0.01	0.03	0.05
PCL18	0.07	0.06	0.07	0.06	0.02	0.03	-0.06	-0.01	0.04	0.05	0.00	-0.02	0.00	-0.02	0.02	0.07	0.09*	0.00	-0.01	-0.05	-0.01	0.01	-0.01	-0.01	0.01
PCL1	0.07	0.04	-0.04	0.04	-0.01	0.01	0.06	0.02	-0.01	0.03	-0.01	0.04	-0.03	-0.02	0.10	-0.01	0.00	0.14	0.04	0.05	-	-	0.02	0.04	0.03

	PCL 1	PCL 3	PCL 4	PCL 5	PCL 6	PCL 7	PCL 8	PCL 9	PCL10	PCL1 1	PCL1 2	PCL1 3	PCL1 4	PCL1 5	PCL1 6	PCL1 7	PCL1 8	PCL1 9	ITQ 1	ITQ 2	ITQ 3	ITQ 4	ITQ 5	CAPS 1	CAPS 2
9															*			*			0.02	0.06			
ITQ1	0.00	-0.01	0.00	0.04	0.12 *	-0.03	-0.07	0.07	-0.02	0.01	0.05	0.13 *	-0.01	0.09 *	-0.06	-0.01	-0.06	0.01	0.07	0.13 *	0.05	0.04	0.01	-0.01	0.05
ITQ2	-0.02	-0.07	-0.01	-0.04	-0.04	0.04	-0.05	-0.01	0.02	-0.03	-0.01	0.02	0.12 *	0.00	-0.03	0.04	0.02	0.01	0.02	0.03	0.01	0.00	0.04	0.01	-0.06
ITQ3	0.07	0.06	0.08	0.06	0.04	0.05	0.09 *	0.01	0.08	0.06	-0.01	0.05	-0.06	0.01	-0.01	0.03	0.04	-0.03	0.08	0.11 *	0.12 *	0.01	- 0.03	-0.01	-0.07
ITQ4	-0.05	-0.04	0.03	0.00	-0.02	0.01	0.00	0.00	0.06	0.03	0.00	-0.04	0.00	0.03	-0.03	0.00	0.03	0.07	0.01	0.01	- 0.03	0.14 *	0.10 *	-0.04	-0.02
ITQ5	0.06	0.06	-0.03	0.01	-0.08	0.03	-0.05	-0.01	-0.07	0.01	0.01	0.06	0.01	0.02	-0.02	-0.02	-0.09 *	-0.09	0.03	- 0.04	0.03	0.09	0.08	-0.03	0.03
CAPS 1	0.03	0.04	0.07	0.02	0.02	0.04	0.04	0.03	-0.02	0.01	0.00	0.01	-0.01	0.07	0.00	-0.01	0.03	0.06	0.02	0.05	0.06	0.03	0.00	0.06	0.05

Note. * illustrates significant edges

Table S3

Temporal network: standard error for fixed effects

	PCL1	PCL3	PCL4	PCL5	PCL6	PCL7	PCL8	PCL9	PCL10	PCL11	PCL12	PCL13	PCL14	PCL15	PCL16	PCL17	PCL18	PCL19	ITQ1	ITQ2	ITQ3	ITQ4	ITQ5	CAPS1	CAPS2
PCL1	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.04	0.05
PCL3	0.05	0.06	0.04	0.04	0.05	0.04	0.04	0.05	0.06	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04
PCL4	0.04	0.04	0.05	0.04	0.05	0.04	0.03	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.04
PCL5	0.05	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05
PCL6	0.04	0.04	0.03	0.03	0.05	0.04	0.03	0.05	0.06	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.04	0.04	0.04	0.04
PCL7	0.04	0.04	0.04	0.04	0.05	0.05	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.05	0.05	0.04	0.04
PCL8	0.04	0.04	0.04	0.03	0.04	0.03	0.06	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.03	0.04	0.03	0.04	0.04	0.04	0.04	0.04
PCL9	0.04	0.05	0.04	0.04	0.05	0.03	0.03	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.05	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.06	0.06
PCL10	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.05	0.03	0.04	0.04	0.05	0.04	0.03	0.04	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.04
PCL11	0.04	0.05	0.05	0.04	0.05	0.04	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.04	0.04	0.05	0.05	0.03	0.04	0.04	0.03	0.04	0.04	0.06	0.06
PCL12	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.06	0.04	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
PCL13	0.04	0.04	0.05	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.04
PCL14	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.03	0.03	0.04	0.04	0.03	0.04	0.04	0.03	0.03	0.04	0.04
PCL15	0.04	0.04	0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.03	0.04	0.04	0.05	0.03	0.04	0.04
PCL16	0.04	0.03	0.04	0.03	0.03	0.03	0.05	0.05	0.03	0.03	0.03	0.03	0.04	0.04	0.05	0.03	0.03	0.03	0.04	0.05	0.03	0.05	0.03	0.03	0.03
PCL17	0.05	0.04	0.05	0.05	0.05	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.06	0.04	0.04	0.05	0.04	0.04	0.05	0.06	0.04	0.04	0.04	0.04	0.05
PCL18	0.04	0.05	0.06	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
PCL19	0.05	0.04	0.04	0.05	0.05	0.04	0.05	0.05	0.06	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.05	0.04	0.04	0.04
ITQ1	0.04	0.04	0.05	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04
ITQ2	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.06	0.04	0.04	0.04	0.05	0.04	0.05	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04
ITQ3	0.04	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.04	0.04	0.04	0.03	0.06	0.05	0.05	0.04	0.04	0.05	0.04

	PCL1	PCL3	PCL4	PCL5	PCL6	PCL7	PCL8	PCL9	PCL10	PCL11	PCL12	PCL13	PCL14	PCL15	PCL16	PCL17	PCL18	PCL19	ITQ1	ITQ2	ITQ3	ITQ4	ITQ5	CAPS1	CAPS2
ITQ4	0.04	0.03	0.04	0.04	0.04	0.03	0.03	0.03	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.04	0.04	0.04
ITQ5	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.04	0.05	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.04
CAPS1	0.05	0.05	0.05	0.03	0.04	0.03	0.03	0.04	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.03	0.04	0.05	0.04	0.04	0.03	0.05	0.07	0.06
CAPS2	0.04	0.04	0.04	0.03	0.04	0.03	0.03	0.03	0.05	0.03	0.03	0.03	0.04	0.04	0.05	0.03	0.03	0.04	0.04	0.04	0.03	0.03	0.04	0.04	0.05

Study III

Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

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Author contributions: G. Werner, I. Göhre, and M. Stefanovic developed the current research question. However, the overall study concept and design was developed by M. Stefanovic, T. Ehring, C. Wittekind, and K. Takano (Study II). Data collection was performed by M. Stefanovic, I. Göhre and, C. Wittekind. M. Stefanovic, K. Takano and, I. Göhre performed the data analysis and interpretation. G. Werner and I. Göhre drafted the manuscript. All authors provided critical revision and approved the final version of the manuscript for submission.

Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

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Author contributions: GGW, IG, and MS developed the current research question. However, the overall study concept and design was developed by MS, TE, CEW and KT (Stefanovic et al., submitted). Data collection was performed by MS, IG and CEW. MS, KT, and IG performed the data analysis and interpretation. GGW and IG drafted the manuscript. All authors provided critical revision and approved the final version of the manuscript for submission.

Study III: Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

Abstract

Objective: There is robust evidence for the influence of sleep disturbances on the maintenance of posttraumatic stress disorder (PTSD). However, little is known about day-to-day variation in trauma-related sleep disturbances (namely insomnia symptoms and nightmares) and their associations with PTSD symptoms. Therefore, we explored the dynamic interplay of these symptoms in daily life using an experience sampling method (ESM). ***Method:*** For 15 consecutive days, patients with a current diagnosis of PTSD (N = 48) reported momentary levels of insomnia symptoms and nightmares as well as PTSD symptoms via a mobile app. ***Results:*** Multilevel model analyses revealed that insomnia and nightmares were significant predictors of PTSD symptomatology on the following day; furthermore, nightmares were predictive of symptoms from each of the four PTSD symptom clusters, namely re-experiencing, avoidance, cognition and hyperarousal as well as symptoms of dissociation. However, PTSD symptoms did not predict insomnia or nightmares during the following night. Multilevel mediation analyses suggested that nightmares mediate the relationship between insomnia and next-day PTSD symptoms. ***Conclusions:*** These findings support accumulating evidence that trauma-related sleep disturbances play an important role in the maintenance of PTSD, by elevating symptoms on a daily basis.

Keywords: Posttraumatic Stress Disorder, sleep disturbances, insomnia, nightmares, experience sampling methodology (ESM)

Clinical impact statements

The current ESM study showed that insomnia and nightmares significantly predicted next-day PTSD symptoms and that the effect of insomnia on PTSD symptom severity was mediated by nightmares. This may suggest that targeting and improving insomnia and nightmares may have a positive effect on daily PTSD symptomatology. Conversely, there was no change in insomnia or nightmares following days with elevated PTSD symptoms. Research and clinical practice may need to recognize insomnia and nightmares as potential treatment targets instead of just as secondary symptoms of PTSD.

Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

Trauma-related sleep disturbances are known to play key roles in the development and maintenance of posttraumatic stress disorder (PTSD) (Biggs et al., 2020; Weber & Wetter, 2021). Traditionally, trauma-related sleep disturbances, conceptualized as symptoms of insomnia (i.e., difficulties falling or staying asleep), and recurrent nightmares have been regarded as secondary symptoms of PTSD (Harvey et al., 2003; Pace-Schott & Bottary, 2018; Spoormaker & Montgomery, 2008). Within the diagnostic criteria of PTSD, these symptoms are included in the hyperarousal and re-experiencing clusters, respectively (i.e., DSM-5, American Psychiatric Association, 2013; ICD-10, World Health Organization, 2004).

However, in the last two decades results from several lines of research have shown that trauma-related sleep disturbances are not just a peripheral phenomenon related to PTSD but rather a core feature that shows an active and dynamic interplay with other PTSD symptoms (Spoormaker & Montgomery, 2008). First, prospective studies showed that symptoms of insomnia experienced before or shortly after a traumatic event increase the risk on an individual developing PTSD and are related to greater symptom severities for the disorder (e.g., Gehrman et al., 2013; Mellman et al., 2002; Wright et al., 2011). Second, after otherwise successful psychological treatment for PTSD insomnia symptoms often remain as residual symptoms in the clinical range (e.g., Pruiksma et al., 2016; Walters et al., 2020; Zayfert & DeViva, 2004). Third, treatment of insomnia symptoms as well as nightmares in PTSD not only decrease these sleep disturbances but also show medium effects for reducing other PTSD symptoms, with stronger effects for nightmare treatment than insomnia treatment (for review, see Ho et al., 2016). Overall, although sleep disturbances are often triggered by a traumatic event and regarded as symptoms of PTSD, these recent findings have led to a

reconceptualization of the role of sleep in PTSD (Germain et al., 2017). This new view suggests that (1) trauma-related sleep disturbances are a risk factor for the development of PTSD and (2) might develop into a separate disorder during the progression of PTSD (Germain, 2013; Sinha, 2016). As such (3) trauma-related sleep disturbances are thought to maintain or even exacerbate other PTSD symptoms, forming a vicious cycle in which sleep disturbances increase the experience of PTSD symptoms and PTSD symptoms lead to increased sleep disturbances (Cox et al., 2017; Spoormaker & Montgomery, 2008).

To establish empirical evidence for the mutual maintenance between sleep and other symptoms, researchers have started using intensive longitudinal assessments where sleep and PTSD symptoms are assessed each day for weeks (e.g., Biggs et al., 2020; Short et al., 2017). First studies using this experience sampling methodology (ESM) have suggested a stronger effect of sleep disturbances on next-day PTSD symptoms compared to the effect of PTSD on subsequent sleep, but findings were not entirely consistent. Four studies showed that different aspects of sleep – namely insomnia symptoms, poor sleep quality, lower sleep efficiency and shorter sleep duration (but not nightmares) – had an effect on increased next-day PTSD symptoms (Biggs et al., 2020; DeViva et al., 2020; Dietch et al., 2019; Short et al., 2017). Two of these studies showed no effect in the reverse direction, indicating that PTSD symptoms did not disturb sleep during the following night (DeViva et al., 2020; Short et al., 2017). However, other studies found that increased PTSD symptoms predicted nightmares (Short et al., 2017; Short et al., 2018), poor sleep quality and shorter sleep duration (Dietch et al., 2019).

In addition to investigating the associations between sleep and overall PTSD symptomatology described above, two ESM studies have also started to explore the associations between sleep and specific PTSD symptom clusters. These studies provide very

preliminary evidence for an effect of some aspects of sleep (i.e., sleep duration, sleep efficiency, sleep quality) on specific PTSD symptom clusters (i.e., hyperarousal, re-experiencing, avoidance and numbing symptoms) (Dietch et al., 2019; Short et al., 2017). In the reverse direction, one study found that all PTSD symptoms clusters predicted worse sleep quality (Dietch et al., 2019).

Taken together, there is inconsistent evidence from previous research about the direction of temporal interactions between sleep and PTSD symptomatology due to highly heterogeneous findings (Biggs et al., 2020; DeViva et al., 2020; Dietch et al., 2019; Short et al., 2017; Short et al., 2018). These mixed findings might be attributed to three factors. First, the studies included very specific study populations (i.e., World Trade responders, current and former military personnel), and only one study included clinical participants with diagnosed PTSD (based on a broad range of traumatic events; $N = 30$). Second, the different studies included various aspects of sleep (e.g., sleep duration, sleep quality, sleep efficiency) but did not focus on trauma-related sleep disturbances specific to PTSD (i.e., insomnia symptoms and nightmares). Third, most studies focused on a single direction of causality instead of exploring the associations bidirectionally.

Consequently, we wanted to investigate bidirectional associations between trauma-related sleep disturbances (i.e., insomnia symptoms and nightmares) and PTSD symptoms in a clinical sample of PTSD patients and expected stronger effects of sleep disturbances on PTSD symptomatology than vice versa. Moreover, we explored the temporal dynamics between insomnia symptoms, nightmares and PTSD symptoms as well as bidirectional associations between trauma-related sleep disturbances and specific PTSD symptom clusters (i.e., re-experiencing, avoidance, hyperarousal, and negative cognitions). The broader goal of

this study was to extend the current knowledge about these daily temporal dynamics to inform future research and clinical practice about the potential role of sleep in PTSD.

Method

Participants

We recruited participants via flyers and advertisement at different inpatient treatment facilities, outpatient treatment centres and trauma support organisations in Munich, Germany, between September 2019 and July 2021. This resulted in a sample of N = 48 participants ($Mage$ = 38.89, $SDage$ = 13.51) all diagnosed with (subsyndromal) PTSD, comprising 35 women (72.92%) and 13 men (27.08%). Participants were mostly treatment seeking (85.42%), but had not yet started with trauma-focused treatment, (for detailed information about data collection and the procedure, please see Stefanovic et al. submitted). Inclusion criteria were age between 18 and 60 years, fluency in the German language, exposure to a traumatic event based on DSM-5 criteria (American Psychiatric Association, 2013) with PTSD (N = 44) or subsyndromal PTSD (N = 4) as the primary diagnosis. Participants were not eligible to participate in the study if they had no memory of the trauma, a current or lifetime diagnosis of schizophrenia or borderline personality disorder, or substance use disorder within the past month and acute suicidality.

Procedure

After a telephone screening, participants were invited for an in-person assessment, received information about the study and provided informed consent. In a first step, the eligibility of participants was assessed using clinical interviews (e.g. SCID) to verify diagnoses of PTSD and other comorbid disorders. If participants met inclusion criteria, they then filled in the sociodemographic and clinical self-report questionnaires. Furthermore, the ESM app was installed on participants' own smartphones or a smartphone provided by the

research team, and participants were instructed on how to use the app interface, and received information about the daily surveys and further study procedures. During the ESM assessment period (15 consecutive days), the app sent four notifications per day at semi-randomized time-points, with each assessment separated by approximately four hours, namely: M1 (i.e., Measurement 1), M2, M3, M4. Depending on their regular sleep time, participants chose the timing of each first assessment to be around 08:30, 9:30, or 10:30 AM. If participants did not respond to the notification, they were reminded to fill out the survey again after 20 minutes. If that reminder was also missed, participants were instructed to respond to the subsequent notification. Participants received 35€ as compensation after completing all smartphone assessments. The study was approved by the ethics committee of the Department of Psychology, LMU Munich.

Measures

Baseline measures

The Structured Clinical Interview for DSM-5 (SCID-5-CV) (Beesdo-Baum et al., 2019) was used to determine current PTSD and other co-morbidities. We conducted all interview sections. When the SCID-5-CV was not available, the Clinician-Administered PTSD Scale for DSM-5 (CAPS-5) (Schnyder & Moergeli, 2002; Weathers et al., 2018) was used to verify the PTSD diagnosis. The CAPS-5 is a structured interview consisting of 30 items. For each item, participants reported the intensity of their symptoms using a 5-point scale (0 = *absent* to 4 = *extremely*).

The PTSD Checklist for DSM-5 (PCL-5) (Krüger-Gottschalk et al., 2017; Weathers et al., 2018) was used to assess PTSD symptoms defined by the DSM-5. The PCL-5 is a self-report measure consisting of 20 items. For each item, participants rate the severity of the symptoms that they have experienced for the past month, using a 5-point scale (0 = *not at all*

to 4 = *extremely*). The total PTSD symptom score is obtained by summing the scores for each of the 20 items. A cut-off value ≥ 33 indicates a clinically significant level of PTSD symptoms.

The Life Events Checklist (LEC-5) (Weathers et al., 2013) is a self-report measure to assess trauma exposure to one of 16 proposed traumatic events and one additional item for which participants could report any other traumatic event if it was not already proposed. Participants could indicate multiple events and could specify whether they had personally experienced, or witnessed the event, whether they had learned about the event happening to a close family member or a friend, whether the event had happened as a part of their job, or if they did had not experienced it at all.

ESM Measures

The instructions for all items were adapted to assess PTSD symptoms experienced since the previous ESM assessment. The first measurement in the morning had a different instruction and targeted symptoms since waking in the morning and sleep symptoms from the previous night. This first assessment included 20 items from the PCL-5 (Krüger-Gottschalk et al., 2017) assessing all symptoms of PTSD according to the DSM-5. It included two additional items from the CAPS-5 (CAPS; Schnyder & Moergeli, 2002), which were adapted for self-reported assessment of dissociation symptoms (i.e., depersonalization and derealization) during ESM assessments. Additionally, two items from the International Trauma Questionnaire (ITQ: Cloitre et al., 2018) assessing disturbances in interpersonal relationships (i.e., feeling distant or cut off from other people; difficulties remaining emotionally close to other people) were also included. Participants reported the intensity of their symptoms on a 5-point-scale (0 = *absent* to 4 = *extremely*).

Predictor and outcome variables used in the models were computed follows: 1) The presence of insomnia symptoms and nightmares during the preceding night were solely assessed at the first measurement point (M1) in the morning of each day with items 20 and 2 of the PCL-5, respectively. 2) The variable "PTSD symptoms" was a sum score of all PCL-5 items except for sleep items (i.e., 2 and 20). To compute the average PTSD symptom severity on each day, the mean of all four daily scores (M1 – M4) was computed. PTSD cluster scores were based on the following combinations of PCL-5 items: re-experiencing (items 1, 3, 4, 5), avoidance (items 6, 7), cognition (items 8 – 14), and hyperarousal (items 15 – 19). These scores were then averaged from all four surveys (M1 – M4) to compute daily scores for each separate PTSD cluster. The two sleep items were removed for the calculation of daily PTSD symptoms and PTSD cluster scores to avoid confounding and conflation of other PTSD measures. Analogously, daily dissociation symptoms (depersonalization, derealization) were computed by combining the two respective items of the CAPS and averaging the scores of all four surveys on a day-level. Disturbances in relationships (emotional disturbances) were similarly computed by summing up the two respective items of the ITQ and then computing a daily average score.

Statistical Analysis

This study represents a secondary analysis of data collected within a larger ESM project (see Stefanovic et al. submitted). First, we calculated a compliance rate for each participant and checked whether there was a systematic pattern in the missingness. Second, all ESM variables that were assessed four times each day (e.g., PTSD symptoms, PTSD cluster scores, etc.) were aggregated to create average day-level scores. As insomnia and nightmares were only collected once a day, no further averaging was needed. For ease of interpretation, all day-level variables were standardized with the grand mean and grand standard deviation.

Further, person-mean centering was used to distinguish between within-person and between-person variance for predictor variables. Outcome variables were only grand-mean standardised in order not to remove between-subject variance. Third, we applied multilevel modelling (MLM) analyses and used the maximum likelihood estimation (Santangelo et al., 2013).

A series of multilevel models were estimated. All multilevel models consisted of two levels. Level 1 was the within-person level (i.e., day-level with repeated measurements) which was nested within the between-person level 2. Each intercept and slope was allowed to vary across individuals. To explore temporal relationships, some variables were cross-lagged, to predict the outcome variable at one time-point "t" by the predictor variable at the previous time-point "t-1" (i.e., the prior day). All multilevel models controlled for the symptoms level of the outcome variable on the prior day (i.e., autocorrelation) on level 1, and for gender and age on level 2.

First, we investigated the effect of insomnia symptoms on next-day PTSD symptomatology while controlling for previous-day PTSD symptoms, gender and age (Model 1.1). In the reverse direction, we tested the prospective effect of daytime PTSD symptoms on insomnia symptoms the following night, while controlling for prior-night insomnia, gender and age (Model 1.2). Second, we investigated the same bidirectional models for nightmares, with nightmares predicting next-day PTSD symptoms (Model 2.1) and daytime PTSD symptoms predicting nightmares (Model 2.2), while controlling for the respective variables. Third, we included insomnia and nightmares as predictors of next-day PTSD symptoms in the same model (Model 3).

These models were estimated to clarify whether the association between trauma-related sleep disturbances and PTSD symptoms was unidirectional or bidirectional. Based on

the results of these models, we aimed to additionally explore a possible vicious cycle between sleep disturbances and PTSD symptoms by investigating the temporal dynamics between insomnia symptoms, nightmares and PTSD symptoms via mediation analyses. As all variables were on level 1, a lower level mediation of lower level effect was established (Kenny et al., 2003). A lower-level mediation model (1-1-1) investigates whether the effect of a predictor variable (X_{tp}) on an outcome variable (Y_{tp}) is mediated via a third variable (M_tp). The "1-1-1 mediation" allows all three causal coefficients (a_p, b_p, c'_p) to be random effects which accounts for heterogeneity in the effect across participants on level 2 as specified by the "p" subscript; the "t" subscript stands for the time-point. The total effect (c = a_p x b_p + c'_p) of X_{tp} on Y_{tp} can be separated into a direct effect (c'_p) of X_{tp} on Y_{tp} and an indirect effect via M_{tp} (a_p x b_p). This indirect effect ("mediation effect") is the product of the effect of X_{tp} on M_{tp} (Walters et al.) and the effect of M_{tp} on Y_{tp} (b_p). To compute confidence intervals for the average indirect and total effects, the Monte Carlo method was used (Preacher & Selig, 2010). This approach by Mackinnon et al. (2004) was adapted to multilevel mediation (Bauer et al., 2006).

Lastly, we conducted exploratory analyses to investigate bidirectional associations between insomnia symptoms, nightmares, and specific PTSD symptom clusters in the same fashion as described for Models 1 – 3.

Results

Sample Characteristics and Compliance

As we did not find systematic missingness, all N = 48 participants were included in the analysis. Participants showed good compliance; the mean number of valid ESM responses was 41.47 (SD = 14.64; range: 5 – 60) out of a total of 60 notifications. Table 1 shows

descriptive statistics of PTSD symptomatology and sleep variables at the baseline assessment and during the ESM phase. For the baseline PCL score, 86.05% participants surpassed the cut-off value ≥ 33, indicating clinically significant PTSD symptoms. During the ESM assessment period, most of the variability in PTSD symptoms was due to individual differences (78% – 82%) as indicated by the intraclass correlations; in other words, these variables had relatively small within-person variability. On the other hand, insomnia symptoms showed larger within-person variability, namely 43% of the total variance.

Table 1

Baseline and ESM Data

Variable	Baseline[a]		ESM[b]		
	M	Range	*M*	Range	*ICC*
Insomnia symptoms	2.80 (1.24)	0 – 4	2.10 (1.08)	0 – 4	.57
Nightmares	2.30 (1.36)	0 – 4	1.56 (1.18)	0 – 4	.68
PTSD symptoms	40.36 (13.41)	8 – 68	26.09 (13.85)	0.77 – 56.34	.81
Re-experiencing	10.29 (3.61)	2 – 16	5.82 (3.97)	0.25 – 14.41	.78
Avoidance	5.41 (2.21)	1 – 8	3.41 (2.13)	0.03 – 8.00	.82
Cognition	14.4 (6.29)	2 – 28	9.91 (5.23)	0.03 – 22.28	.80
Hyperarousal	9.96 (4.06)	0 – 18	6.94 (3.94)	0.12 – 14.60	.81
Dissociation symptoms	0.69 (1.03)	0 – 3	1.28 (1.39)	0.00 – 4.87	.75
Disturbances in Relationships	–	–	2.86 (1.92)	0.00 – 6.61	.77

Note. *N* = 48; *M* = mean; *SD* = standard deviation; *ICC* = intraclass correlation.

See method section for a detailed description of the composition of listed variables. Sleep

items were excluded from computation of PTSD symptom severity and PTSD cluster scores at baseline and ESM was also done in the multilevel models. All ESM variables display within-person daily means (average of M1-M4), except for insomnia and nightmares which display within-person means at the first measurement M1;

[a] n = 43. [b]n = 48.

Multilevel Models

Bidirectional Associations Between Sleep Disturbances and PTSD Symptoms

All of the following multilevel models were controlled for the covariates described in the methods section. The effects of these control variables (e.g., prior-day symptoms, gender and age) can be found in the supplementary material (Table S2). As displayed in Table 2, insomnia symptoms significantly predicted next-day PTSD symptoms. However, PTSD symptoms during the day had no effect on insomnia symptoms during the following night. Similarly, nightmares were a significant predictor of elevated PTSD symptoms on the next day. Conversely, PTSD symptoms showed no effect on subsequent nightmares. Of note, when including both sleep variables in the adjusted models, the effect of insomnia symptoms became insignificant and only nightmares remained as predictor of next-day PTSD symptoms, $B = 0.24$, $SE = 0.05$, 95% CI [0.15, 0.34], $p < .001$ (Table S2).

Table 2

Adjusted Multilevel Models of the Bidirectional Associations Between Trauma-Related Sleep Disturbances and PTSD Symptoms

Predictor	*B*	*SE*	*p*	95% CI
Outcome: PTSD symptoms				
Insomnia symptoms	**0.15**	**0.03**	**< .001**	**0.08, 0.22**
Nightmares	**0.26**	**0.05**	**< .001**	**0.17, 0.35**
Outcome: Insomnia symptoms				
PTSD symptoms	0.11	0.16	.512	-0.22, 0.42
Outcome: Nightmares				
PTSD symptoms	0.21	0.14	.147	-0.08, 0.49

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors. All predictors are entered into separate models that control for covariates. Namely, models are adjusted for prior-day PTSD symptoms or the respective prior night's sleep disturbance on level 1 as well as for gender and age on level 2.

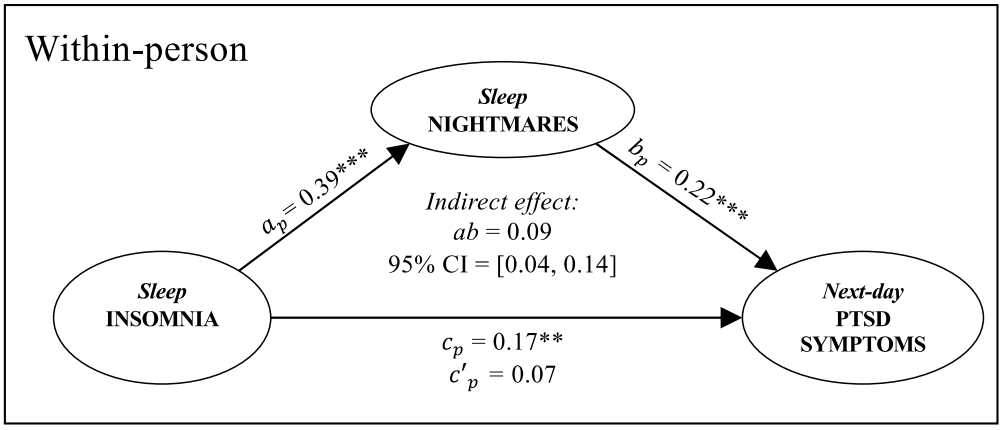
Multilevel Mediation Models of the Interrelations between Insomnia, Nightmares and PTSD Symptoms

Based on these results, the temporal dynamics between insomnia symptoms, nightmares and PTSD symptoms were explored using two multilevel mediation analyses (i.e., effect of insomnia on PTSD via nightmares as well as the effect of nightmares on PTSD via insomnia). First, there was no significant indirect effect of nightmares on next-day PTSD symptoms through insomnia symptoms, B = 0.07, 95% CI [-0.02, 0.08]. However, in the reverse direction, nightmares displayed a full mediation of significantly accounting for the association between insomnia symptoms and next-day PTSD symptoms (Figure 1). Specifically, insomnia significantly predicted increased nightmares (a_p path, B = 0.39, SE = 0.05, p < .001), which in return were associated with higher next-day PTSD symptoms (b_p path), B = 0.22, SE = 0.05, p < .001). The total effect of insomnia on next-day PTSD symptoms (c_p path, B = 0.17, SE = 0.05, p < .01) was reduced to a direct effect (c'_p path) of B

= 0.07 (*SE* = 0.04, *p* = .069) after adjusting for the indirect effect via nightmares (*ab* path, *B* = 0.09, 95% CI [0.04, 0.14]).

Figure 1

Multilevel Mediation Analysis



Note. Multilevel mediation analysis with unstandardized beta values (a_p, b_p, c_p, c'_p) evaluating the indirect effect of insomnia symptoms on next-day PTSD symptoms through nightmares.

Bidirectional Associations Between Sleep Disturbances and PTSD Symptom Clusters

Similar to the associations between sleep disturbances and global PTSD symptoms, insomnia symptoms and nightmares both had a significant influence on next-day PTSD symptoms for each symptom cluster in separate models (Table 3), controlling for prior-day symptoms, gender and age. However, in all combined models, once again the effect of insomnia symptoms on each cluster and symptom (i.e., re-experiencing, avoidance, cognition, hyperarousal, symptoms of dissociation) became insignificant after adding nightmares as predictor (see Supplementary Table S3). Only disturbances in relationships were more strongly predicted by insomnia symptoms (*B* = 0.08, *SE* = 0.04, 95% CI [-0.00, 0.16], *p* = .040), as the association with nightmares became insignificant after combining both predictors.

Table 3

Adjusted Multilevel Models of Night-Time Insomnia Symptoms or Nightmares Predicting Next-Day PTSD Symptom Clusters

Model Predictor [a]	*B*	*SE*	*p*	95% CI
Outcome: Re-experiencing				
Insomnia symptoms	**0.17**	**0.04**	**< .001**	**0.09, 0.25**
Nightmares	**0.32**	**0.04**	**< .001**	**0.23, 0.41**
Outcome: Avoidance				
Insomnia symptoms	**0.13**	**0.03**	**< .001**	**0.06, 0.20**
Nightmares	**0.22**	**0.04**	**< .001**	**0.13, 0.30**
Outcome: Cognition				
Insomnia symptoms	**0.12**	**0.03**	**< .001**	**0.06, 0.19**
Nightmares	**0.20**	**0.05**	**< .001**	**0.11, 0.30**
Outcome: Hyperarousal				
Insomnia symptoms	**0.13**	**0.04**	**.002**	**0.06, 0.21**
Nightmares	**0.21**	**0.05**	**< .001**	**0.11, 0.29**
Outcome: Dissociation symptoms				
Insomnia symptoms	**0.10**	**0.04**	**.037**	**-0.00, 0.18**
Nightmares	**0.24**	**0.08**	**.003**	**0.09, 0.39**
Outcome: Disturbances in relationships (DR)				
Insomnia symptoms	**0.11**	**0.03**	**< .001**	**0.05, 0.17**
Nightmares	**0.13**	**0.05**	**.009**	**0.04, 0.23**

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors.

[a] The two predictors (i.e., insomnia symptoms and nightmares) are entered into separate models which control for covariates. Namely, all models are adjusted for prior-day PTSD severity or the respective symptom cluster on level 1 as well as gender and age on level 2.

In the reverse direction (supplementary Table S4), re-experiencing, avoidance, and cognition were not significant predictors of either insomnia symptoms or nightmares when controlling for the respective prior night's sleep disturbance, gender and age. Only daytime hyperarousal, *B* = 0.28, *SE* = 0.12, 95% CI [0.02, 0.54], *p* = .035, and symptoms of dissociation, *B* = 0.29, *SE* = 0.12, 95% CI [0.01, 0.53], *p* = .035, were significantly associated with subsequent nightmares.

Discussion

The current study investigated associations between daily trauma-related sleep disturbances (i.e., insomnia symptoms and nightmares) and PTSD symptomatology in a clinical sample of PTSD patients. Results showed that insomnia and nightmares predicted PTSD symptoms on the following day in separate models. However, when including both predictors in the same model, only nightmares predicted PTSD symptoms. Additionally, we explored a possible vicious cycle between insomnia symptoms, nightmares, and PTSD symptoms. Interestingly, we only found an effect of insomnia symptoms on PTSD symptoms mediated by nightmares but no effect of nightmares on PTSD via insomnia symptoms. Regarding the effect of PTSD symptoms on sleep, PTSD symptoms did not predict insomnia symptoms or nightmares during the subsequent night. Overall, the same pattern of results was found for almost all PTSD symptom clusters with a unidirectional influence of sleep on PTSD but not vice versa.

Earlier research suggests that trauma-related sleep disturbances develop after experiencing a traumatic event (e.g., Sinha, 2016) and are partly a direct consequence of other PTSD symptoms in clinical samples. However, increasing evidence shows that insomnia symptoms are a predictor of other mental disorders, including PTSD (e.g., Hertenstein et al., 2019). Our results converge with earlier findings that have shown that daily insomnia symptoms or other aspects of sleep quality are predictors of next-day PTSD symptoms, with no or smaller effects of PTSD on subsequent sleep (Biggs et al., 2020; DeViva et al., 2020; Dietch et al., 2019; Short et al., 2017). Therefore, the findings are generally in line with the recent conceptual shift in research now emphasizing the central and independent role of sleep disturbances in the maintenance and exacerbation of daily PTSD symptoms.

Of note, however, in our study, the effect of insomnia symptoms on PTSD was only present in a reduced model with insomnia as the only sleep-related predictor, but not when insomnia and nightmares were simultaneously included as predictors in the model. Nightmares, on the other hand, continued to predict PTSD symptoms even when insomnia symptoms were controlled for. Previous studies had only investigated the effect of insomnia symptoms on PTSD symptoms (e.g., Biggs et al., 2020; DeViva et al., 2020; Dietch et al., 2019) or looked at the effects of insomnia and nightmares separately (Short et al., 2017). Therefore, the temporal dynamics between daily insomnia symptoms, nightmares and PTSD symptoms remained largely unknown. The findings obtained in the current study indicate that insomnia symptoms are predicting next-day PTSD via increased nightmares. Interestingly, this is somewhat in line with a recent study investigating predictors of posttraumatic nightmares in a daily assessment study (Youngren et al., 2020). They found that increased time to fall asleep interacted with cognitive pre-sleep arousal to predict nightmare occurrence. This might indicate that increased time to fall asleep that is filled with cognitive pre-sleep arousal (i.e., ruminating about trauma- or nightmare-related contents) enhances the probability of nightmares.

Nightmares were a strong predictor of next-day PTSD symptoms, however, no effect of PTSD on subsequent nightmares was found in the reverse direction. This is in contrast to earlier studies investigating bidirectional associations between nightmares and PTSD that found an effect of PTSD symptoms on nightmares during the following night (Short et al., 2017; Short et al., 2018). However, it is in line with other studies using objective sleep assessments emphasizing that nightmares are independently associated with PTSD symptom severity and explain a significant amount of variance within PTSD symptoms (e.g., Germain

et al., 2008; Krakow et al., 1995; Krakow et al., 2004). Therefore, more ESM studies are needed to elucidate the direction of causality between nightmares and daily PTSD symptoms.

We also investigated bidirectional associations between trauma-related sleep disturbances and specific PTSD symptom clusters and additional symptoms (dissociation, disturbances in relationships). As insomnia symptoms and nightmares are each part of one PTSD symptom cluster (the hyperarousal cluster and the re-experiencing cluster, respectively), more pronounced associations with other symptoms from these clusters appeared plausible. However, no specificity in the relationship between these sleep-related symptoms and PTSD was found for the different symptom clusters. Instead, we found that insomnia symptoms and nightmares both predicted symptoms from each of the four PTSD symptom clusters in separate models. However, when including both predictors in one model, only nightmares continued to predict symptoms from every PTSD symptom cluster. In the inverse direction, only effects of hyperarousal and dissociation on nightmares were found. This effect of hyperarousal is in line with a previous ESM study in which daytime hyperarousal predicted worse sleep quality at night (Dietch et al., 2019). Moreover, according to cross-sectional studies PTSD patients with more severe hyperarousal show significantly more sleep disruptions (Van Wyk et al., 2016) and nightmares (Babson et al., 2011).

Overall, these additional findings are partly in line with two earlier studies that found some effects of sleep quality on specific PTSD clusters (Dietch et al., 2019; Short et al., 2017), but they are in contrast to other findings from one of these studies showing effects from, all PTSD clusters on subsequent sleep quality (Dietch et al., 2019).

Limitations

Some limitations need to be considered when interpreting the current findings. First, as this project is based on secondary analyses of another study, we only measured insomnia symptoms and nightmares each via one item from the PCL-5 on a 5-point scale, which might limit variability in responses. In addition, insomnia symptoms comprised difficulties initiating and maintaining sleep, therefore we are not able to differentiate between these two aspects of sleep disturbances. Second, in line with most earlier studies in the field insomnia symptoms and nightmares were collected at the same time in the morning after awakening. However, the experience of having a nightmare might influence the overall perception of sleep. In future studies, it would be interesting to also include objective variables and physiological parameters of sleep. Third, we were not able to investigate other related aspects such as daily maladaptive cognitions and behaviour (e.g., fear of sleep) or pre-sleep arousal in this study. Particulary since, as more than half of our sample indicated sexual assault as index trauma, aspects like fear of sleep might play an additional important role. Therefore, these results cannot be generalized to all other traumatic experiences without caution. Fourth, our study only provides information about the maintenance of PTSD symptoms; assumptions about the development of trauma-related sleep disturbances and PTSD symptoms are based on earlier research. Fifth, this study did not control for psychotropic medication as we did not expect it to change within the 15 days of EMA assessment. However, as sedating and psychotropic medications (e.g., antidepressants) can affect trauma-related sleep disturbances in PTSD patients (van Liempt et al., 2006), we reported medications with an influence on sleep in the supplementary Table S1 (Pagel & Parnes, 2001).

Conclusion

The present findings support daily insomnia symptoms and nightmares as predictors of next-day PTSD symptoms in individuals diagnosed with PTSD. We further extend the current literature by showing that only nightmares continued to predict PTSD symptoms when both sleep-related predictors were simultaneously included. Interestingly, the effect of insomnia symptoms on PTSD symptoms was mediated by nightmares, indicating that insomnia symptoms increase the probability of nightmare occurrence, which enhances PTSD symptoms the next day. Regarding specific PTSD symptom clusters, similar unidirectional associations were found for almost all clusters, except for hyperarousal and dissociation symptoms which showed bidirectional associations with nightmares. Overall, treating trauma-related sleep disturbances in addition to PTSD symptoms is an important treatment component that may reduce insomnia symptoms and nightmares and enhance remission rates. Therefore, sleep disturbances should be further investigated in future research and clinical practice as potential treatment targets due zo their independent effect on daily PTSD symptoms.

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Temporal Associations Between Trauma-Related Sleep Disturbances and Posttraumatic Stress Disorder (PTSD): An Experience Sampling Study

Supplementary Material

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Table S1
Sample Characteristics (N = 48)

Characteristics	*Mean (SD) or N (%)*
Age (years, M, SD)	38.89 (13.51)
Gender (n, %)	
Women	35 (72.92%)
Men	13 (27.08%)
Education (n)[a]	
Middle school or equivalent	21 (43.75%)
High school degree	13 (27.08%)
University degree	12 (25%)
Type of traumatic events experienced (n) [a]	
Accident	3 (6.25%)
Physical assault	11 (22.92%)
Sexual assault	28 (58.33%)
Life-threatening illness or injury	2 (4.17%)
Any other very stressful event or experience	2 (4.17%)
Comorbidity disorders (n)	
Depression	12 (25%)
Obsessive compulsive disorder	4 (8.3%)
Substance use disorder	4 (8.3%)
Anxiety disorder	4 (8.3%)
ADHD	1 (2.08%)
Treatment setting (n) [c]	
Inpatients	15 (31.25%)
Outpatients	26 (54.17%)
Not in treatment	7 (14.58%)
Medication [a]	
Current psychopharmacological medication	18 (39.13%)
Sedatives and hypnotics (i.e., Lorazepam, Diazepam, Zolpidem, Promethazine)	6 (13.04%)
Antidepressants (i.e., Amitriptyline, Mirtazapine, Fluoxetine, Paroxetine, Sertraline, Citalopram, Venlafaxine, Bupropion, Valdoxan, Trazodone)	12 (26.09%)
Neuroleptics (i.e., Quetiapine, Risperidone, Prothipendyl)	5 (10.87%)
Other sleep medications and OTC sleep medications	2 (4.35%)
Opioids (i.e., Morphine)	1 (2.17%)
Use of other medications (e.g., thyroid preparations, anticonvulsants, antihypertensives, pain medication)	13 (28.26%)

[a] n = 46.
ADHD= Attention Deficit Hyperactivity Disorder, OTC = over the counter. Note that counts of patients using medication might not add up due to polypharmacy (i.e., some patients were receiving multiple psychotropic drugs of different classes and/ or other medications).
[c] Participants were in assessment phase and did not start with trauma focused treatment yet.

Table S2

Adjusted Multilevel Models of the Bidirectional Associations Between Trauma-Related Sleep Disturbances and PTSD Symptoms Including all Predictors

Predictor	*B*	*SE*	*p*	95% CI
Outcome: PTSD symptoms				
Insomnia symptoms	0.04	0.03	.220	-0.03, 0.10
Nightmares	**0.24**	**0.05**	**< .001**	**0.15, 0.34**
Prior-day PTSD symptoms	**0.30**	**0.06**	**< .001**	**0.16, 0.43**
Gender	0.10	0.13	.451	-0.17, 0.36
Age	**0.28**	**0.13**	**.036**	**0.01, 0.54**
Outcome: Insomnia symptoms				
PTSD symptoms	0.11	0.16	.512	-0.22, 0.42
Prior-night insomnia	-0.09	0.06	.114	-0.22, 0.02
Gender	0.07	0.12	.591	-0.17, 0.31
Age	0.17	0.12	.170	-0.07, 0.41
Outcome: Nightmares				
PTSD symptoms	0.21	0.14	.147	-0.08, 0.49
Prior-night nightmares	-0.10	0.08	.227	-0.26, 0.06
Gender	0.05	0.13	.685	-0.21, 0.32
Age	0.13	0.13	.320	-0.12, 0.39

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors.

Table S3

Adjusted Multilevel Models of Night-Time Insomnia Symptoms and Nightmares Predicting Next-Day PTSD Symptom Clusters Including all Predictors

Predictors	*B*	*SE*	*p*	95% CI
Outcome: Re-experiencing				
Insomnia symptoms	0.03	0.03	.379	-0.04, 0.10
Nightmares	**0.30**	**0.05**	**< .001**	**0.21, 0.39**
Prior-day re-experiencing	**0.22**	**0.06**	**< .001**	**0.11, 0.33**
Gender	0.11	0.13	.401	-0.14, 0.36
Age	**0.31**	**0.13**	**.019**	**0.06, 0.55**
Outcome: Avoidance				
Insomnia symptoms	0.04	0.03	.250	-0.03, 0.11
Nightmares	**0.20**	**0.05**	**< .001**	**0.10, 0.29**
Prior-day avoidance	**0.26**	**0.06**	**< .001**	**0.14, 0.38**
Gender	0.08	0.13	.513	-0.17, 0.34
Age	**0.29**	**0.13**	**.028**	**0.04, 0.53**
Outcome: Cognition				
Insomnia symptoms	0.04	0.03	.184	-0.02, 0.10
Nightmares	**0.17**	**0.05**	**.001**	**0.07, 0.27**
Prior-day cognition	**0.30**	**0.06**	**< .001**	**0.18, 0.41**
Gender	0.09	0.13	.511	-0.16, 0.33
Age	0.23	0.13	.079	-0.03, 0.51
Outcome: Hyperarousal				
Insomnia symptoms	0.06	0.03	.087	-0.01, 0.12
Nightmares	**0.17**	**0.04**	**< .001**	**0.08, 0.26**
Prior-day hyperarousal	**0.41**	**0.04**	**< .001**	**0.29, 0.53**
Gender	0.13	0.14	.360	-0.15, 0.40
Age	0.25	0.14	.069	-0.02, 0.52
Outcome: Dissociation symptoms				
Insomnia symptoms	0.00	0.03	.886	-0.06, 0.08
Nightmares	**0.23**	**0.08**	**.005**	**0.08, 0.38**
Prior-day dissociation sym.	0.24	0.06	**< .001**	0.12, 0.37
Gender	0.04	0.12	.749	-0.22, 0.31
Age	0.03	0.12	.782	-0.20, 0.28
Outcome: Disturbances in relationships (DR)				
Insomnia symptoms	**0.08**	**0.04**	**.040**	**-0.00, 0.16**
Nightmares	0.09	0.06	.146	-0.04, 0.20
Prior-day DR	**0.31**	**0.07**	**< .001**	**0.17, 0.42**
Gender	-0.14	0.13	.279	-0.39, 0.10
Age	0.10	0.13	.454	-0.16, 0.39

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors.

Table S3

Adjusted Multilevel Models of Daytime PTSD Symptom Clusters Predicting Insomnia Symptoms

Predictor	*B*	*SE*	*p*	95% CI
Outcome : insomia symptoms				
Re-experiencing	0.13	0.13	.329	-0.14, 0.40
Prior-night insomnia	-0.17	0.06	.218	-0.20, 0.05
Gender	0.08	0.12	.528	-0.17, 0.32
Age	-0.07	0.41	.179	-0.07, 0.41
Outcome : insomia symptoms				
Avoidance	0.22	0.15	.145	-0.07, 0.52
Prior-night insomnia	-0.10	0.06	.094	-0.22, 0.02
Gender	0.08	0.13	.550	-0.17, 0.33
Age	0.17	0.13	.173	-0.07, 0.42
Outcome : insomia symptoms				
Cognition	-0.10	0.14	.456	-0.41, 0.17
Prior-night insomnia	-0.09	0.06	.139	-0.22, 0.03
Gender	0.06	0.12	.634	-0.17, 0.29
Age	0.16	0.12	.634	-0.07, 0.39
Outcome : insomia symptoms				
Hyperarousal	0.16	0.14	.264	-0.13, 0.46
Prior-night insomnia	-0.09	0.06	.118	-0.21, 0.03
Gender	0.08	0.12	.531	-0.17, 0.33
Age	0.18	0.12	.165	-0.07, 0.42
Outcome : insomia symptoms				
Dissociation symptoms	0.12	0.12	.315	-0.14, 0.35
Prior-night insomnia	-0.05	0.06	.413	-0.17, 0.07
Gender	0.07	0.12	.567	-0.16, 0.30
Age	0.18	0.12	.159	-0.06, 0.41
Outcome : insomia symptoms				
Disturbances in relationships	0.02	0.11	.828	-0.21, 0.23
Prior-night insomnia	-0.04	0.06	.474	-0.17, 0.08
Gender	0.09	0.13	.499	-0.16, 0.33
Age	0.17	0.13	.181	-0.08, 0.41

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors.

Table S4

Adjusted Multilevel Models of Daytime PTSD Symptom Clusters Predicting Nightmares

Predictor	*B*	*SE*	*p*	95% CI
Outcome : nightmares				
Re-experiencing	0.16	0.12	.187	-0.08, 0.39
Prior-night nightmares	-0.09	0.08	.296	-0.26, 0.08
Gender	0.03	0.13	.819	-0.23, 0.29
Age	0.09	0.13	.486	-0.16, 0.34
Outcome : nightmares				
Avoidance	0.10	0.12	.388	-0.15, 0.34
Prior-night nightmares	-0.06	0.08	.434	-0.15, 0.34
Gender	0.04	0.13	.332	-0.23, 0.10
Age	0.12	0.13	.368	-0.14, 0.38
Outcome : nightmares				
Cognition	0.10	0.12	.408	-0.15, 0.34
Prior-night nightmares	-0.06	0.07	.429	-0.21, 0.09
Gender	0.04	0.13	.741	-0.23, 0.32
Age	0.13	0.13	.329	-0.13, 0.39
Outcome : nightmares				
Hyperarousal	**0.28**	**0.12**	**.035**	**0.02, 0.54**
Prior-night nightmares	-0.07	0.08	.353	-0.231, 0.08
Gender	0.05	0.13	.692	-0.21, 0.32
Age	0.13	0.13	.338	-0.13, 0.39
Outcome : nightmares				
Dissociation symptoms	**0.29**	**0.12**	**.035**	**0.01, 0.53**
Prior-night nightmares	-0.07	0.08	.371	-0.24, 0.08
Gender	0.02	0.13	.853	-0.18, 0.36
Age	0.10	0.13	.470	-0.18, 0.36
Outcome : nightmares				
Disturbances in relationships	0.12	0.11	.314	-0.12, 0.34
Prior-night nightmares	-0.04	0.07	.591	-0.18, 0.10
Gender	0.05	0.13	.707	-0.22, 0.33
Age	0.13	0.13	.339	-0.13, 0.39

Note. *B* = unstandardized coefficient; *SE* = unstandardized standard error; *p* = p-value; 95% CI = confidence interval. Bold values represent significant predictors.

Study IV

Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

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Study IV: Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

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Study IV: Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Abstract

A reciprocal relationship between repetitive negative thinking (RNT) and negative affect has been found in various types of psychopathology. Recent studies have suggested that the magnitude of this association can vary across time and individuals, which may inform future psychopathology. Here, we explored how these dynamics and interplays are manifested in student and general populations using a statistical clustering algorithm. Across three experience-sampling datasets, our clustering analyses consistently identified two groups of individuals; one group had a higher bidirectional association between RNT and negative affect (and also higher inertia) than the other group. Furthermore, a prospective analysis revealed that the group with the higher bidirectional association is at risk of developing depressive symptoms during the three-month follow-up period if they had experienced high levels of negative affect over the experience-sampling phase. These findings suggest that the dysfunctional affective and cognitive dynamics would be a promising target of preventative intervention.

Keywords: repetitive negative thinking, negative affect, vector-autoregressive model, alternating least square algorithm

Is A High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Repetitive negative thinking (RNT) is found to be elevated across various mental disorders, and is now regarded as an important transdiagnostic process (Ehring & Watkins, 2008; Harvey & Watkins, 2004). RNT conceptually covers *depressive rumination*, which is defined as "repetitive and passive thinking about one's symptoms of depression and the possible causes and consequences of these symptoms" (Nolen–Hoeksema, 2004, p. 107), and *worry*, namely "a chain of thoughts and images, negatively affect-laden, and relatively uncontrollable" (e.g., Borkovec et al., 1983, p. 10). Traditionally, worry and rumination have been studied in isolation from a disorder-focused perspective (e.g., rumination in depression; worry in anxiety). However, there is now broad evidence that both rumination and worry are transdiagnostic phenomena in that they are associated with, and even predict, a wide range of psychopathology, including depression, anxiety, insomnia, and binge eating (e.g., Borkovec et al., 1998; Carney et al., 2006; Hoyer et al., 2002; Nolen-Hoeksema et al., 1993; Nolen-Hoeksema, 2000; Purdon & Harrington, 2010; Roberts et al., 1998). On the other hand, there are somewhat different views in the literature regarding the precise nature of the relationship between worry and rumination. Whereas some authors suggest that they are best regarded as distinct – albeit related – processes (e.g., Papageorgiou & Wells, 1999), others have proposed that worry and rumination are two variants of the same underlying process that can be defined as *repetitive negative thinking* (RNT) (e.g., Ehring & Watkins, 2008). Importantly, the latter view suggests that the process characteristics of RNT that worry and rumination have in common are responsible for its dysfunctional effects, rather than the disorder-specific content. There is now accumulating evidence supporting this view (e.g., McEvoy et al., 2018;

Spinhoven et al., 2018; Topper et al., 2014). The current study was therefore also based on the concept of RNT as a transdiagnostic process.

For the past decades, research has explored how RNT contributes to psychopathology, and one of the most robust findings in the literature is that RNT increases negative affect (NA) (Huffziger et al., 2013; Nolen-Hoeksema & Morrow, 1993). Furthermore, research has established a feedback loop of NA enhancing RNT (e.g., Moberly & Watkins, 2008), which is part of the definition of depressive rumination as a response to dysphoria (e.g., (Nolen-Hoeksema, 2000; Nolen-Hoeksema et al., 2008). This bidirectional association is supported by studies using Experience Sampling Method (ESM) (Reed & Csikszentmihalyi, 2015), which is a standard approach to observing participants' moment-to-moment psychological experiences and their dynamics in daily life settings. In a typical design, participants report their current feelings, thoughts, and/or behavior via mobile devices in response to signals that are emitted several times per day for one or two weeks. Using ESM, Moberly and Watkins (2008) showed that ruminative self-focus in a moment predicts NA in the next moment and vice versa, although other ESM studies suggested that the effect of RNT on affect may vary across the types of RNT (i.e., rumination vs. worry) (Kircanski et al., 2018) and may have substantial individual differences (Pasyugina et al., 2015). Furthermore, the increased association between RNT and NA is highlighted as a precursor of depression. A single-case study using ESM suggested that worry becomes more strongly associated with positive and negative affect as a sudden shift in depressive symptoms (or the moment of relapse) approaches (Wichers & Groot, 2016). This strong association is regarded as an early warning sign that informs a near-future transition into depression, which is typically accompanied by other statistical features, such as increased autocorrelation (so-called inertia) in the repeatedly

assessed cognition and affect scores (van de Leemput et al., 2014; Wichers, 2014; Wichers et al., 2019).

Note that an early warning sign was originally studied as a "state" predictor, which can vary across time within a person. However, the same phenomenon (i.e., RNT-NA association) has been related to individual differences in depressive symptoms (Moberly & Watkins, 2008) and neuroticism in personality (Bringmann et al., 2013), which therefore could be used to identify individuals who are at high risk of developing psychopathology in the future (Brose et al., 2015; Pasyugina et al., 2015)[6]. Despite the potential predictive value, it is largely unknown how the rigidity in the association between RNT and NA is manifested in a population and whether individuals with such rigidity are to develop psychopathology over time.

In the current study, we applied a statistical clustering method to three ESM datasets in order to explore how individuals in student and general populations can be clustered on the basis of the strength of the RNT-NA associations; and we also tested whether these clusters are predictive of future depressive symptoms. As our focus was on examining RNT-NA associations as indicators of risk for developing depressive symptoms (and not a marker of current psychopathology), we collected data in non-clinical populations. In addition, unlike previous studies relating depressive symptoms to the unidirectional effect of RNT on NA or that of NA on RNT separately (e.g., Moberly & Watkins, 2008; Pasyugina et al., 2015), we used a clustering approach (a) to demonstrate that there is a group of individuals showing the bidirectional relationship between RNT and NA, and (b) to explicitly test how vulnerable

[6] We are not suggesting that the within-person and between-person phenomena are necessarily in parallel (cf. Simpson's paradox). Instead, we were interested in whether the cognitive/affective dynamics assessed at a given time point hold a predictive value for psychopathology. Also, it was not possible to explicitly distinguish between the trait and state nature of the dynamics in RNT and NA, because our ESM assessments were too short to model a temporally varying association between RNT and NA.

those individuals are for depressive symptomatology. Although clustering on an ESM dataset has been rarely conducted, an exceptional study (Bulteel et al., 2016) clustered individuals for the day-to-day associations between various depressive symptoms (e.g., loss of energy, poor sleep quality, rumination). They identified two groups of individuals in their non-clinical sample; one was labeled as "rigid responders" showing higher associations between the symptoms, whereas the other group was "flexible responders" with lower symptom associations.

Another important dimension in a model of affective dynamics is the autoregressive components of the outcome variables; e.g., the effect of NA at a given time point predicting NA at the next moment. This auto-regressive effect is understood as (emotional) inertia, representing the degree to which affect (and cognition) is resistant to change over time (Kuppens et al., 2010). Studies found that high emotional inertia is a good predictor of the current and future levels of depressive symptoms (Koval et al., 2012; Kuppens et al., 2012). Van de Leemput et al. (2014) also found that emotional inertia was elevated among general as well as clinical populations who consequently experienced significant changes in depressive symptoms. Because inertia is known to be predictive of psychopathology, our clustering also considered the two inertia (or auto-regressive) parameters for RNT and NA as well as the two directional (or cross-regressive) effects of RNT on NA and of NA on RNT.

As an overview, we analyzed three ESM datasets across Studies 1–3. In Study 1, we explored potential clusters of individuals who share similar dynamics features for worry and NA, as assessed via ESM. Study 2 aimed to replicate the findings of Study 1 on another ESM dataset with slightly different items, i.e., focusing on RNT instead of worry. The goal of Study 3 was to test the risk of the identified group(s) to develop depressive symptomatology at a 3-month follow-up. This prospective analysis was performed in order to extend our

knowledge of the predictive value of the combined dynamics features, which has been almost exclusively based on the cross-sectional evidence. (e.g., (Bringmann et al., 2013; Bulteel et al., 2016; Moberly & Watkins, 2008)

Study 1

The purpose of Study 1 was to cluster individuals on the basis of the dynamics of worry and NA. In this ESM study, we assessed momentary levels of worry and NA 10 times per day for 4 days. We expected that the clustering would identify a group of individuals who are characterized by the bidirectional relationship between worry and NA, although we did not have a specific hypothesis for the number and types of clusters that would emerge in the analyzed sample.

Method

Participants. In total, 142 participants were recruited via flyers distributed in the buildings of LMU Munich, online university portals, and social networking services. In the flyers, it was stated that the aim of the study was to investigate the relationship between worry and mood in participants' daily lives. There were no specific inclusion and exclusion criteria. The majority of participants were psychology students (40%). We did not perform a priori power analysis to design the sample size because of the exploratory nature of this study. However, our sample size was larger than that of Bulteel et al. (2016), who used the same clustering method to the current study and found the cluster of rigid responders among 56 participants.

Twelve participants were excluded from the data analyses for the following reasons: (a) aborted participation and/or technical problems with software (N = 10); (b) low compliance with ESM, 5 or fewer responses (N = 2). The final sample size was N = 130: 15 men and 115 (88.5 %) women. The mean age was 23.9 years (SD = 5.7).

Measures.

Momentary negative affect. Momentary levels of NA were assessed by the following eight items: *anger, disgust, fear, sadness, tension, shame, guilt,* and *disgust* (Gross & Levenson, 1993; Llera & Newman, 2014). Participants rated the extent to which each item represented their current mood using a 5-point Likert scale (1= *not at all* to 5 =*very much*).

Worry. Momentary levels of worry were assessed by the following three questions: (a) How much did you worry in the past 30 min?; (b) How much did you feel bothered by worrying in the past 30 min?; and (c) How uncontrollably did you experience worry in the past 30 min? These items were adapted from previous ESM studies focusing on worry, reflecting each dimension of impairment and uncontrollability for the current worrisome thoughts (Pieper et al., 2007, 2010; Szabó & Lovibond, 2002; Thielsch et al., 2015; Verkuil et al., 2007). Importantly, these earlier studies established the good psychometric properties of the worry items, e.g., convergent validity for the association with trait measures of worry. Each item was rated on a 5-point Likert scale (1= *not at all* to 5 = *very much*).

Both worry and NA scales exhibited good reliability in the current data: Rkf = 0.99 and Rc = 0.72 for NA; Rkf = 0.99 and Rc = 0.87 for worry (Shrout & Lane, 2012).

Baseline questionnaires.

Penn State Worry Questionnaire (PSWQ; **Meyer et al., 1990; Stöber, 1995).** The PSWQ is a self-report questionnaire consisting of 16 items designed to measure a general tendency to worry. The items capture the intensity, impairment, and uncontrollability of worry (e.g., "*When I am under pressure, I worry a lot"*; "*Many situations make me worry"*), which are rated on a 5-point Likert scale (1 = *not at all typical for me* to 5 = *extremely typical for me*). The internal consistency was very good (α = .91).

Perseverative Thinking Questionnaire (PTQ; Ehring et al., 2011). The PTQ is a 15-item questionnaire designed to assess repetitive negative thinking. Participants rate each item (e.g., "*The same thoughts keep going through my mind again and again*") on a 5-point Likert scale (0 = *never* to 4 = *almost always*). The questionnaire showed a very high internal consistency (α = .93).

State-Trait Anxiety Inventory (STAI; Spielberger, 1983). The STAI is a self-administered questionnaire assessing long-term chronic levels of anxiety (STAI-T) and current level of anxiety (STAI-S) with 20 items each. Participants rate statements such as "*I feel calm*" or "*I am worried*" on a 4-point Likert scale (1= *not at all* to 4 = *very much*). The internal consistency was good for both scales (α = .91 and α = .90, respectively).

Beck Depression Inventory II (BDI II; Beck et al., 1996). The BDI is a 21-item questionnaire assessing the symptoms of depression at the affective, cognitive, behavioral, somatic, and motivational levels, as well as additional suicidal thoughts within the past two weeks. For each item, different statements are provided and participants are asked to choose the most appropriate variant, e.g., from 0= *I am not sad* to 3= *I'm so sad or unhappy that I can not stand it*. The internal consistency was good (α = .88).

Procedure. Upon arrival at the lab, participants received an explanation of the study procedure and then provided written informed consent. Next, participants completed the baseline questionnaires. The 4-day ESM phase started on the next day of the baseline assessment. Participants received 10 signals per day on the mobile phones, which prompted participants to respond to questions concerning their current moods and thoughts.

These ESM signals were emitted 10 times per day from 10 AM to 10 PM at semi-randomized intervals of around 1 hour. Participants had to enter their responses within 5 minutes of receiving each signal emission, although they could choose to answer within the 5

minutes or to postpone it once for a maximal 15 minutes. MovisensXS software (Movisens Ltd., 2016; Versions 0.4.2437 and 0.7.416) was used to control the signals and to record participants' responses.

After completing the ESM assessment, participants received course credit or monetary compensation (average €20), whereby the amount of the compensation was discounted according to the number of uncompleted signals. The study protocol was approved by the ethics committee of the Department of Psychology at LMU Munich.

Statistical analyses. Our statistical analyses consisted of the following three steps: (a) clustering individuals via the alternating least squares (ALS) algorithm on ESM-assessed worry and NA (Bulteel et al., 2016); (b) testing whether each dynamics parameter varied across the identified groups; and (c) exploring group differences in depressive symptomatology. The ALS algorithm clusters individuals on the basis of the estimates of a vector auto-regressive (VAR) model. Here, the VAR model was specified as two regression models; either worry or NA at time *t* was predicted by worry and NA at time *t-1*. This formulation provides the following four dynamics parameters; i.e., two auto-regressive effects (for worry and NA) and two cross-regressive effects (of worry on NA and of NA on worry). In order to keep the interval between time *t* and *t-1* consistent, the initial responses on each day were not included in the analyses.

The ALS algorithm fits the VAR model separately on given groups of participants and then the algorithm updates the group partitioning in search of the (local) minimum residuals of the VAR models. This means that the ALS algorithm requires the number of groups and initial group partitioning as hyper-parameters prior to the optimization routine. Users may give a specific number of groups from their knowledge about the data, or they may evaluate the goodness of fit for each number of groups exhaustively (see the next paragraph). The

group partitioning is typically given by random group assignment and/or a hierarchical clustering method (e.g., Ward method) on individual VAR estimates per participant. In each step of the optimization routine, a VAR model is estimated on each of the partitioned groups, whose residuals are evaluated to update the group partitioning; that is, the algorithm searches the best partitioning that minimizes the sum residual across all groups.

The number of groups is determined by the CHull procedure (Ceulemans & Kiers, 2006; Wilderjans et al., 2013), which searches the maximum scree test (*st*) ratio. The *st* ratio evaluates relative information gain when adding one extra group. This ratio score can be defined for any number of groups that the user of the ALS algorithm assumes. The local maximum of *st* ratios indicates the number of groups that best explains the data, as this means that adding another group does not improve the model fit meaningfully.

The CHull procedure considers the complexity of the models, which selects the smallest number of groups with a (locally) maximum explanation of the data. A disadvantage of this procedure is that by default, it cannot select the model with the lowest complexity, i.e., the model with only one group (Wilderjans et al., 2013). For example, the *st* ratio for the model with two groups ($k = 2$) is given as the relative reduction in the sum residual form $k = 1$ to $k = 2$, to the reduction from $k = 2$ to $k = 3$. As the model with $k = 0$ does not exist (i.e., zero group in a dataset), an *st* ratio cannot be defined for $k = 1$. To circumvent this zero-complexity issue, Wilderjans et al. (2013) suggested including in the comparison an even simpler model, such as a regression without any predictors but only with an intercept. At the same time, they warned that this null model should not be too simple in order to avoid an inflation of the *st* ratio at $k = 1$. Following this recommendation, we defined the null ($k = 0$) model to have the intercept and auto-regressive (but not cross-regressive) effects, as we were more interested in the cross-regressive effects in the current analyses.

All variables used in the ALS clustering were first standardized with the grand means and *SD*s (for comparability across studies using different measures of RNT and NA), and then person-mean centered to specifically focus on the intra-individual dynamics in worry and NA. The person-mean centering eliminates the individual differences in the mean levels of the predictors, which allows for estimating the auto- and cross-regression effects without the influences of the between-person variance.

As the second step of the analyses, group differences in the auto- and cross-regression coefficients were tested by multilevel models (see for more details, (Takano et al., 2020)). We estimated two multilevel models that are parallel to the VAR model used in the ALS clustering; that is, (a) worry at time *t* was predicted by worry and NA at time *t-1*, and (b) NA at time *t* was predicted by worry and NA at time *t-1*. On top of this Level-1 structure, the models included ALS-assigned group memberships as a Level-2 predictor and their interactions with worry and NA as cross-level interactions. Each auto- and cross-regression coefficient was assumed to vary across participants (i.e., random effects). We were specifically interested in the cross-level interactions, which clarified whether the auto- and cross-regressive coefficients significantly differed across groups. We also tested the conditional effects (or simple slopes) of worry and NA for each group in order to determine whether the worry-NA association is unidirectional or bidirectional (or null) for each group (Preacher et al., 2006). We used the R package, lme4 (Bates et al., 2015), to estimate the models with restricted maximum likelihood estimation.

The third step of the analyses was to relate the ALS-identified groups to concurrent levels of psychopathology. We performed simple t-tests to explore the group differences in depressive symptoms and other psychopathology measures.

Results

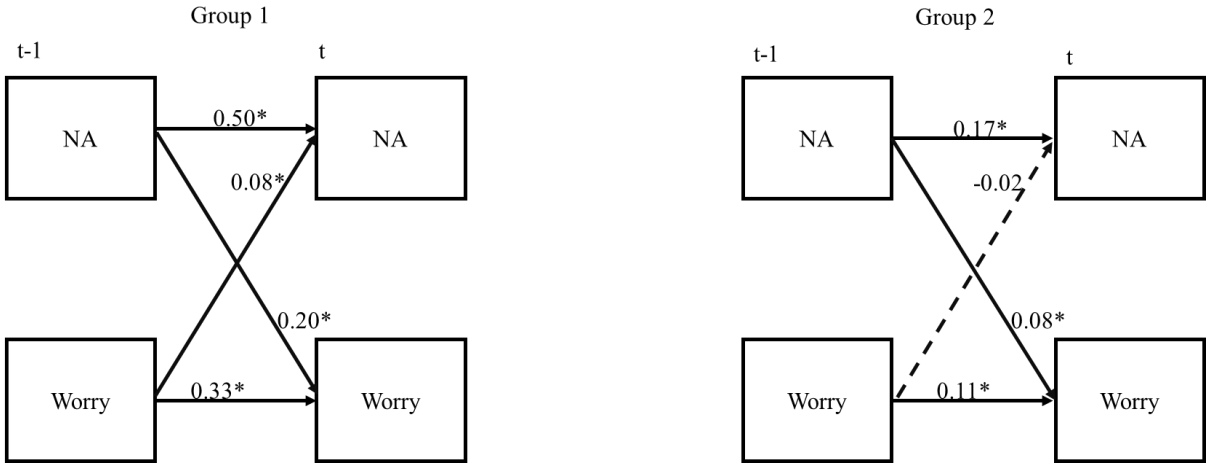
Descriptives and compliance. There were 24 participants who had a BDI-II score above the cut-off (> 13) for moderate levels of depressive symptoms (Beck et al., 1996). As for the compliance with ESM, we calculated the mean number of ESM responses across participants, which was 37.26 (*SD* = 3.86;) out of 17-43 ESM signals that were actually sent to each participant. Given that most participants received more than 35 signals over the ESM period, the lower limit of the observed compliance rate was regarded as approximately 40% (cf. Study 2). Due to system errors, some participants received more than the scheduled number (i.e., 40) of signals (*N* = 15), which made the response-to-response intervals more variable than we initially planned. Because a VAR model assumes that intervals between consecutive measurements are of equal length (e.g., Bulteel et al., 2016), we excluded 30 responses that were too close to the previous responses (i.e., made within 30 min of the previous response). We also excluded 198 responses that were made more than 120 min after the previous response (e.g., when a response was missing).

ALS clustering. First, we clustered participants using the ALS algorithm for the worry and NA dynamics. To determine the number of clusters, we examined the sum residuals for *k* = 0 – 4 clusters, showing the largest reduction between *k* = 1 and 2. Indeed, the CHull procedure indicated *k* = 2 as the best model, with *st* ratios of 0.20, 2.37, and 1.83 for *k* = 1, 2, and 3, respectively.

Second, we estimated two multilevel models where either NA or worry at time *t* was predicted by NA and worry at time *t-1* as well as their cross-level interactions with the ALS groups. Figure 1 represents the estimated auto- and cross-regressive effects for each group.

Figure 1

Groups identified by the ALS algorithm



Note. Group 1 (N = 53) is characterized by higher auto- and cross-regression coefficients than Group 2 (N = 77; the group differences were statistically significant for all regression coefficients). * p < .05, indicating that the coefficient is significantly different from zero.

When predicting NA at time *t*, both NA and worry at time *t-1* had significant cross-level interactions with the groups, suggesting that the auto-regressive effect of NA is higher in Group 1, B = 0.50, SE = 0.03, t = 14.72, p < 0.01, than in Group 2, B = 0.17, SE = 0.03, t = 5.81, p < 0.01. Similarly, the effect of worry on NA is higher in Group 1, B = 0.08, SE = 0.03, t = 3.08, p < 0.01, than in Group 2, B = -0.02, SE = 0.02, t = - 0.81, p = 0.42.

When predicting Worry at time *t*, both NA and Worry at time *t-1* had significant cross-level interactions with the groups, suggesting that the effect of NA on worry is higher in Group 1, B = 0.20, SE = 0.03, t = 5.90, p < 0.01, than in Group 2, B = 0.08, SE = 0.03, t = 2.90, p < 0.01. The auto-regressive effect of worry is higher in Group 1, B = 0.33, SE = 0.03, t = 11.62, p < 0.00, than in Group 2, B = 0.11, SE = 0.03, t = 3.93, p < 0.01. Taken together, Group 1 is characterized by a bidirectional relationship between worry and NA, whereas Group 2 has overall smaller auto- and cross-regressive coefficients with only a significant unidirectional effect of NA on worry.

A series of *t*-tests (see Table S1 for the complete results) showed significant group differences in the baseline questionnaire scores as well as the mean levels of the ESM variables. Compared to the participants in Group 2, those in Group 1 (i.e., the group characterized by the bidirectional relationship between worry and NA) had significantly higher levels of: (a) worry assessed by ESM (Cohen's $d = 0.53$); (b) worry assessed by the PSWQ ($d = 0.39$); and (c) depressive symptoms assessed by the BDI-II ($d = 0.39$). However, the group differences in the PTQ and STAI did not reach statistical significance (ds = 0.22, 0.24).

Discussion

In Study 1, the ALS algorithm identified two groups. Compared to Group 2, Group 1 showed higher bidirectional associations between worry and NA, as well as higher levels of inertia for both worry and NA. Furthermore, Group 1 had significantly higher mean levels of worry and also exhibited higher levels of depressive symptoms than Group 2. These findings may suggest that a rigid association between negative affect and cognition, combined with their temporal stability, can be an important feature of depressive symptomatology.

Study 2

The primary aim of Study 2 was to test the robustness of the clustering results that we found in Study 1. Specifically, we tested whether the two groups of high vs. low associations between worry and NA could be replicated in another ESM study, where we assessed momentary levels of RNT and NA eight times per day for two weeks. The main difference from Study 1 was that the ESM items assessed the broader transdiagnostic concept of RNT rather than the more specific, future-oriented process of worry (Ehring & Watkins, 2008; Harvey & Watkins, 2004).

Method

Participants. We analyzed the ESM data collected by Rosenkranz et al. (2020) for a different research question. The sample consisted of 150 participants aged between 18 and 40 years (M = 22.46, SD = 4.01; 66.8% women) who had been recruited via posters and online announcements in Munich, Germany. The parent study was advertised as a "smartphone study" investigating rumination that occurs in everyday life. Inclusion criteria were that participants were fluent in German and that they were currently not in treatment for mental disorders. The latter criterion was applied because our Ethics Committee raised the concern that frequent assessments of mood and RNT in the ESM phase might affect highly vulnerable individuals and/or negatively impact on the treatment they were receiving.

Responses from 30 participants were excluded from statistical analyses for the following reasons: currently being in psychological treatment (N = 1); non-completion of the ESM assessment due to technical problems and/or personal reasons (N = 9); low response rate of less than 40% to ESM signals (N = 9); and repetition of the same response on more than one item throughout the course of the ESM assessment (N = 11). Thus, the final sample size was N =120 (71% women) with the mean age of 22.25 years (SD = 3.89). The study protocol was approved by the local ethics committee at the Department of Psychology at LMU Munich.

Measures.

Momentary negative affect. Participants rated their momentary levels of affect using two items that assessed valence and arousal. Each item was rated on a bipolar scale: for valence, the choices ranged from 1 = *discontent / bad* to 7 = *content / well*; for arousal, the choices ranged from 1 = *agitated / tense* to 7 =*calm/relaxed* (Huffziger et al., 2012; Wilhelm & Schoebi, 2007). A previous study established good reliability of these items (Wilhelm & Schoebi, 2007).

Repetitive negative thinking. Momentary levels of RNT were assessed by four items of subjective burden, repetitiveness, intrusiveness, and difficulty disengaging from RNT. The item assessing subjective burden ("*How much do you feel weighed down by these thoughts at this moment?*" (Thielsch et al., 2015) was rated on a 7-point Likert scale (1 = *not at all* to 7 = *very much*). The other three items were from the PTQ, which covers the core components of dysfunctional RNT (Ehring et al., 2011): repetitiveness *("The same thoughts keep going through my mind again and again*"), intrusiveness ("*Thoughts come to my mind without me wanting them to*"), and difficulty disengaging from negative thoughts ("*I get stuck on certain issues and can't move on*"). The time frame was "at this moment" for all items (i.e., *"Please indicate to what degree these statements apply to you at this moment"*).These items were rated on a 7-point Likert scale (1 = *not at all* to 7 = *very much*). Both NA and RNT scales exhibited good reliability in the current data: Rkf = 0.99 and Rc = 0.51 for NA; Rkf = 0.99 and Rc = 0.84 for RNT. The original studies providing data for Studies 2 and 3 had the aim to investigate the psychometric properties of the momentary RNT measure. The EMA RNT scale was significantly correlated with trait measures of worry and RNT (i.e., PSWQ: r=.30); PTQ: r=.37); for detailed information on psychometric properties of the momentary RNT and NA measure, see Rosenkranz et al. 2020).

Baseline questionnaires.

Patient Health Questionnaire (PHQ-9; Kroenke et al., 2001) is a symptom depression checklist for a current depressive episode. Participants are asked to indicate for a total of nine items (e.g., *feeling down, depressed,* or *hopeless*) how much they were bothered by given problems in the last two weeks (response format: "*not at all*", "*several days*", "*more than half the days*", "*nearly every day*"). The internal consistency was $\alpha = .78$.

Seven-item Generalized Anxiety Disorder Scale (GAD-7; Spitzer et al., 2006) is a self-report questionnaire assessing symptoms of generalized anxiety disorder. Participants rate how often in the last 2 weeks they have felt bothered by the problems listed, from 0 (*Not at all*) to 3 (*Nearly every day*). Internal consistency was moderate with α = .78.

Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990; Stöber, 1995). *See description in Study 1.* Internal consistency was good with α = .90.

Perseverative Thinking Questionnaire (PTQ*; *Ehring et al., 2011). *See description in Study 1.* Internal consistency was good with α = .93.

Procedure. In the first meeting, participants received an explanation of the study procedures, including how to use the ESM application on a smartphone. Participants then provided written informed consent, and subsequently completed the baseline questionnaires. The ESM phase started on the day following the first appointment and lasted for 14 consecutive days. During this period, participants received eight signals per day, which prompted them to complete the ESM measures. The signals were emitted with pseudorandomized intervals of approximately two hours. The initial signal was sent around 10 AM on weekdays and 12 AM on weekends; the last signals were scheduled around 10 PM on working days and 12 PM on weekends. After receiving each signal, participants had to start answering the ESM questions within 15 minutes. Reminders were sent 5 and 10 minutes after each signal emission unless participants had responded to the signal.

Participants received course credit or €8 per hour for face-to-face appointments, and included in a lottery for a voucher (4 online-shopping vouchers worth €50 each), whereby their chances in the lottery depended on their compliance rate in ESM.

Statistical analyses. We used the same analytic approach as in Study 1. First, we performed the ALS clustering. Second, we estimated multilevel models in order to test which

regression coefficients significantly differed between the ALS-identified groups. Third, we examined the group differences in depressive symptoms (for a detailed description, see Study 1). Prior to the analyses, we standardized and person-mean centered the ESM-assessed variables. To keep the response-to-response intervals constant, we excluded responses that were made more than 200 minutes after the previous response.

Results

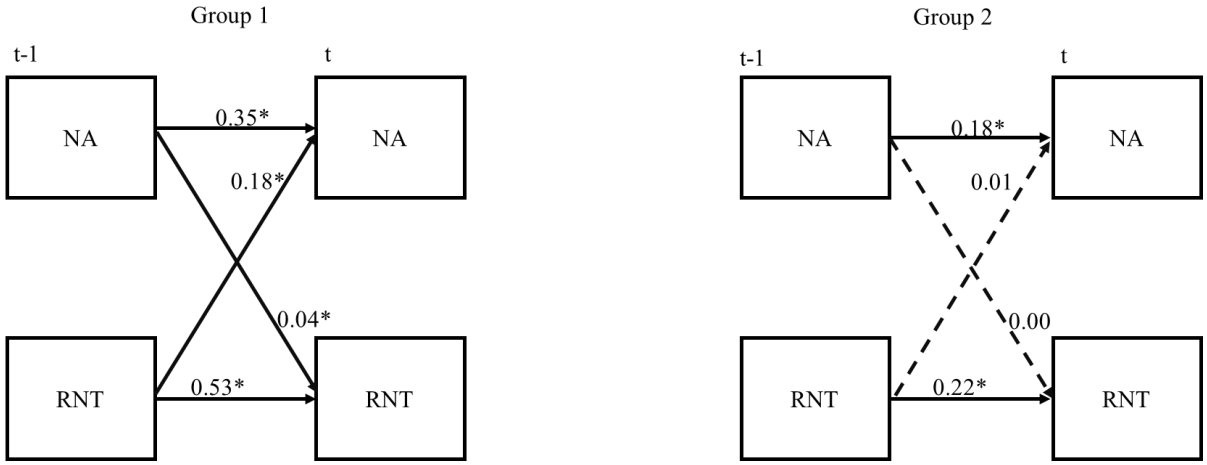
Descriptives and compliance. There were 13 participant who had a PHQ-9 score at the baseline assessment above the cut-off (≥ 10) for moderate levels of depressive symptoms (Kroenke et al., 2001). The mean compliance rate for the ESM assessment was 74% (*SD* = 0.21) after excluding invalid responses.

ALS clustering. First, we applied the ALS algorithm to cluster participants on the basis of the RNT and NA dynamics. The CHull procedure indicated *st* ratios of 0.20, 3.51, and 1.13 for 1, 2, and 3 clusters, respectively. This replicates our findings in Study 1 that two clusters fit the data better than one or three clusters.

Second, we estimated multilevel models where either RNT or NA at time *t* was predicted by (a) RNT and NA at time *t-1* and (b) their cross-level interactions with the ALS-assigned group memberships. The estimated auto- and cross-regressive effects for each group are presented in Figure 2.

Figure 2

Groups identified by the ALS algorithm



Note. Group 1 (*N* = 87) was characterized by higher auto- and cross-regressive coefficients than Group 2 (*N* = 99; the group differences were statistically significant for all regression coefficients except for the effect of NA_{t-1} on RNT_t). *$p < .05$, indicating that the coefficient is significantly different from zero.

When predicting NA at time *t*, both NA and RNT at time *t-1* had significant cross-level interactions with the groups, suggesting that the auto-regressive effect of NA is higher in Group 1, *B* = 0.35, *SE* = 0.02, *t* = 16.00, *p* < 0.01, than in Group 2, *B* = 0.18, *SE* = 0.02, *t* = 7.90, *p* < 0.01. The effect of RNT was also higher in Group 1, *B* = 0.18, *SE* = 0.02, *t* = 7.90, *p* < 0.01, than in Group 2, *B* = 0.01, *SE* = 0.02, *t* = 0.64, *p* = 0.53.

When predicting RNT at time *t*, only the auto-regressive effect (i.e., the effect of RNT at time *t-1*) showed a significant group difference, suggesting that the effect is higher in Group 1, *B* = 0.53, *SE* = 0.01, *t* =22.50, *p* < 0.01, than in Group 2, *B* = 0.22, *SE* = 0.02, *t* = 9.71, *p* < 0.01. Although the interaction between NA at time *t-1* and the groups did not reach statistical significance (*p* = 0.09), the effect of NA on RNT was significant in Group 1, *B* = 0.04, *SE* = 0.01, *t* =2.34, *p* = 0.02, but not in Group 2, *B* = 0.00, *SE* = 0.02, *t* = 0.00, *p* > 0.99. These results suggest that Group 1 can be characterized by the bidirectional association

between RNT and NA, whereas Group 2 has overall smaller auto- and cross-regressive effects without significant association between NA and RNT.

Third, we tested whether the ALS groups differed in the baseline depression and other psychopathology measures (see Table S2). A series of *t*-tests indicated that there were no significant group differences in the baseline questionnaires or in the person mean levels of ESM-assessed RNT and NA ($|d|$s < 0.26).

Discussion

The results of the ALS clustering replicated the two-cluster findings from Study1, highlighting Group 1 to have higher associations between RNT and NA, as well as higher levels of inertia for both RNT and NA, than Group 2. However, unlike Study 1, Group 2 had no significant association between RNT and NA (note that Group 2 in Study 1 had a significant unidirectional effect of NA on worry). Another difference was that in Study 2, there were no significant group differences in depressive symptoms (or in any other psychopathology measures) at the baseline. Similarly, no group differences were identified for the person mean levels of RNT and NA during the ESM period.

Results showed good consistency for the clustering outcomes between Studies 1 and 2, distinguishing a group with a bidirectional relationship between RNT and NA as well as high inertia, from a second group with lower inertia and rigidity. However, the implications of these differences for symptomatology remain unclear, as the group differences in the symptomatology that we found in Study 1 were not replicated in Study 2. Although these inconsistencies could be explained by the difference in the ESM items (i.e., RNT vs. worry), a critical limitation of both studies was the lack of follow-up assessment. Note that we did not explicitly expect significant group differences in the concurrent levels of depressive symptoms and other psychopathology measures. This is because a rigid association between

RNT and NA as well as elevated inertia has been considered as a precursor of symptom changes that take place in the future (e.g., van de Leemput et al., 2014; Wichers & Groot, 2016). Therefore, a cross-sectional group difference is not a necessary condition to establish the predictive value of our clustering approach.

To this end, a test on the prospective effect of the ALS groups was warranted to ultimately determine whether the clustering approach is informative to study psychopathology. The goals of Study 3 were first to replicate the clustering findings from Studies 1 and 2, and second, to extend the results from the first two studies by testing prospective associations between the ALS groups and depressive symptoms.

Study 3

We performed an ESM study where momentary levels of RNT and NA were assessed 5 times per day for 10 days. We followed up participants for three months after the completion of the ESM assessment, which allowed for testing the prospective effect of the ALS groups on depressive symptoms. Specifically, we hypothesized that the group with a bidirectional association between RNT and NA would show higher levels of depressive symptoms at the follow-up time point, compared to the group with the unidirectional (or no) association between RNT and NA.

When testing the prospective effect of the ALS groups, we were also interested in the person means of RNT and NA. Given the recent findings that a single index of affective dynamics is *not* a better predictor of well-being than the mere person mean of the affect (Dejonckheere et al., 2019), we controlled the effects of the person means in our prospective analysis. Furthermore, as the dynamics parameters (and the ALS groupings) seem to be overall independent of the person means of RNT and NA (Study 2; Table S2), our prospective analysis also tested the interaction between the person means and ALS groups. This

interaction would clarify whether people with higher mean NA and/or RNT would be more vulnerable for depressive symptomatology within the bidirectional group. Such a vicious cycle has been highlighted in the theories and empirical findings of depressive rumination (e.g., Moberly & Watkins, 2008); i.e., RNT and NA influence each other, escalating into and self-maintaining a very high, pathological level. Thus, we expected that the group with highly rigid and inert dynamics of RNT and NA would be most vulnerable for depressive symptoms when combined with elevated mean levels.

Method

Participants. We analyzed part of unpublished ESM data (Rosenkranz et al., in prep). In this study, 220 participants aged 18–35 years (M = 21.34, SD = 3.50; 76 % women) were recruited via posters and online announcements. In these advertisements, participants were informed that the aims of the study were to assess rumination and worry in daily life and to test whether these negative thinking styles would predict depressed mood and anxiety at a future time point. Inclusion criteria were: (a) being a native German speaker, (b) being enrolled as a student at a university, (c) being between 18 and 35 years old, and (d) not currently suffering from any mental disorders (see also the Participants section of Study 2). Despite these inclusion criteria, two participants indicated that they suffered from a mental disorder at the baseline assessment; these participants were not invited to the ESM phase. For statistical analyses, we excluded data from participants who had low compliance with the ESM assessment: i.e., those who had a response rate of less than 60% (N = 10)[7]; repeated the same response to more than one item throughout the ESM assessment (N = 22). The final

[7] We found that the compliance rate was very good: Median = 0.90 (SD = 0.13). Participants excluded due to the criterion that the compliance rate was smaller than the median minus 2 SD (i.e., < 0.60) were clear outliers. Additionally, we performed a sensitivity analysis with the cutoff of < 0.40, which is compatible to the lower limit or the cut-off in Study 1 and 2, which showed that the results were unchanged in terms of the clustering and the prospective effect on depressive symptoms (for detailed results, see supplementary material).

sample consisted of 186 participants (*M* = 21.18, *SD* = 3.34, 76% women). The study protocol was approved by the local ethics committee of the Department of Psychology at LMU Munich.

Measures. The same measures as in Study 2 were used in the current study. The baseline assessment and follow-up included the PHQ-9 (α = .72), GAD-7 (α = .81), PSWQ (α = .90), and PTQ (α = .94). In the ESM assessment, RNT was measured by the same four items of subjective burden, repetitiveness, intrusiveness, and difficulty disengaging from RNT, with only slight differences in phrasing. Both NA and RNT scales exhibited good reliability in the current data: Rkf = 0.98 and Rc = 0.60 for NA; Rkf = 0.99 and Rc = 0.90 for RNT (Shrout & Lane, 2012) .

Procedure. Data was collected in the following three phases: (a) baseline assessment at the start of a semester (teaching term); (b) ESM immediately following baseline assessment, and (c) follow-up assessment, during an exam period which was approximately three months after the baseline assessment. We scheduled the follow-up in this way because one of the aims of the overarching study was to examine the effect of increased stress for students (exam) on relationship between rumination and negative affect. During the first appointment, participants received an explanation of the study procedures and provided written informed consent. They then completed the baseline questionnaires and received an introduction to how to use the ESM application on a smartphone. The ESM period started on the day after the baseline assessment and continued for 10 consecutive days. During this ESM phase, participants received five signals per day, prompting them to fill in brief questionnaires for RNT and NA. The initial signal of a day was sent around 9 AM, 10 AM, or 11 AM, depending on each participant's preference. The rest of the signals were emitted with pseudorandomized intervals of approximately 2 hours over a 10-hour time window.

Participants had to answer questions about their current levels of affect and RNT, and the occurrence of a negative event since the previous signal. Participants received three reminders (i.e., 5, 10, and 20 minutes) after the first notification if they had not answered the question, and had 30 minutes to answer. The follow-up assessment was conducted online at the end of the same semester (i.e., around three months after the baseline assessment) and took place during the exam period. The same questionnaires used during the baseline were repeated. Participants received €8 per hour or course credit for basement and follow-up assessments. In addition, they also had a chance to win extra Amazon vouchers (4 vouchers worth €50 each) in the lottery, whereby their chances of winning depended on their compliance rate in ESM.

Statistical analyses. We used overall the same statistical approach as in Studies 1 and 2. We first applied the ALS algorithm to identify groups on the basis of RNT and NA dynamics. Second, we estimated multilevel models to establish the group differences in the auto- and cross-regressive coefficients. Third, group differences in baseline depressive symptomatology were explored. Prior to the analyses, all ESM-assessed variables were standardized and person-mean centered. We excluded responses that were made more than four hours after the previous response in order to keep the response-to-response intervals constant.

To test the prospective effect of the ALS groups, we estimated regression models, in which follow-up depressive symptoms were predicted by (a) the baseline symptoms, (b) person means of RNT and NA over the ESM course, (c) the dummy-coded group memberships given by the ALS algorithm, and (d) the interactions between the person means and ALS groups.

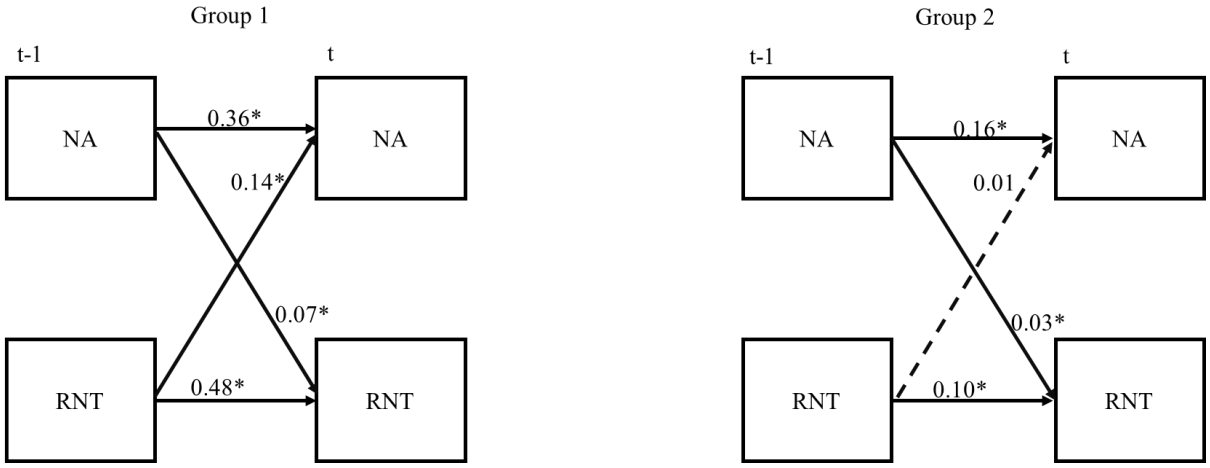
Results

Descriptives and compliance. Twenty-nine participants had a PHQ-9 score equal or greater than the cut-off (≥ 10) for moderate levels of depressive symptoms at the baseline assessment; at the follow-up, 64 participants scored equal or greater than the cut-off (Kroenke et al., 2001). The mean compliance rate for the ESM assessment was 87% (*SD* = 13).

ALS clustering. The CHull procedure indicated *st* ratios of 0.09, 2.47, and 1.69 for 1, 2, and 3 clusters, respectively. This replicates the findings from Studies 1 and 2 that two clusters fit the data better than one or the other number of clusters. We estimated multilevel models where either RNT or NA at time *t* was predicted by (a) RNT and NA at time *t-1* and (b) their cross-level interactions with the ALS groups. Figure 3 represents the estimated auto- and cross-regressive effects for each group.

Figure 3

Groups identified by the ALS algorithm



Note. Group 1 (N = 87) was characterized by higher auto- and cross-regressive coefficients than Group 2 (N = 99; the group differences were statistically significant for all regression coefficients except for the effect of NA on RNT). * $p < .05$, indicating that the coefficient is significantly different from zero.

In predicting NA at time *t*, both NA and RNT at time *t-1* had significant interactions with the groups, suggesting that the auto-regressive effect of NA is higher in Group 1, B = 0.36, SE = 0.02, t = 15.73, $p < 0.01$, than in Group 2, B = 0.16, SE = 0.02, t = 7.01, $p < 0.01$. The effect of RNT is higher in Group 1, B = 0.14, SE = 0.02, t = 5.99, $p < 0.01$, than in Group 2, B = -0.02, SE = 0.02, t = -0.74, p = 0.46.

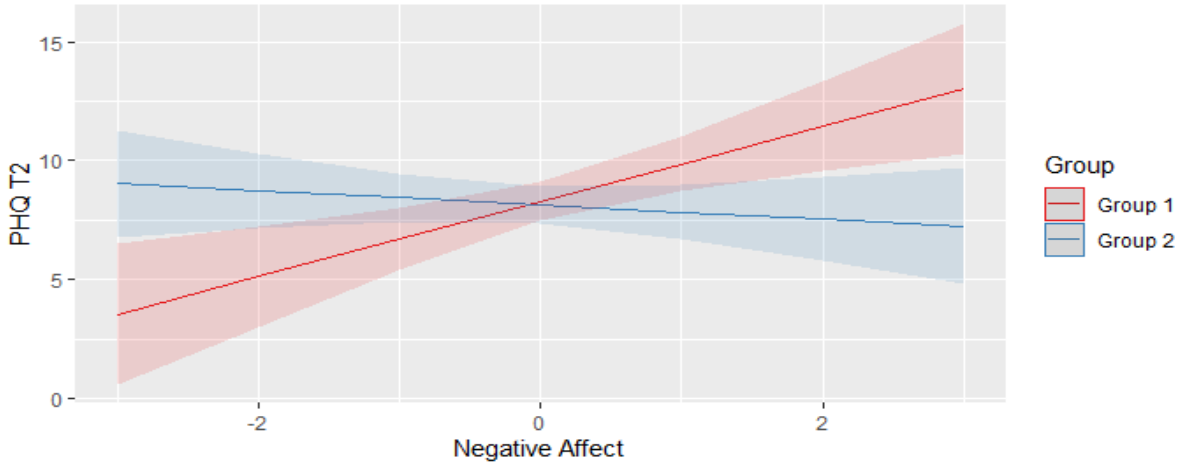
When predicting RNT at time *t*, only RNT (but not NA) at time *t-1* showed a significant interaction with the groups, suggesting that the auto-regressive effect of RNT is higher in Group 1, B = 0.48, SE = 0.02, t = 20.87, $p < 0.01$, than in Group 2, B = 0.10, SE = 0.02, t = 4.11, $p < 0.01$. The effect of NA on RNT did not significantly differ between the two groups: for Group 1, B = 0.07, SE = 0.02, t =3.87, $p < 0.01$; for Group 2, B = 0.03, SE = 0.02,

t = 2.01, p = 0.04. These results suggest that Group 1 is characterized by the bidirectional association between NA and RNT, whereas Group 2 has overall smaller auto- and cross-regressive effects with a statistically significant unidirectional effect of NA on RNT. Additionally, we tested whether the ALS groups differ in the levels of depressive symptomatology at the baseline assessment (see Table S3). A series of *t*-tests showed that there were no significant differences between the two groups, either in the questionnaire scores or in the person means of RNT and NA (|d|s < 0.26).

Prospective analysis. To test the prospective effect of the ALS groups, we estimated a regression model with the follow-up depressive symptoms as the outcome and with the person mean of NA, the ALS groups, and their interaction as the predictors. Here we controlled for the baseline levels of depressive symptoms. The person mean of RNT was not included in the model, which had a moderate-to-high correlation with the person mean of NA and could cause multicollinearity. The ALS groups were dummy-coded as 0 for Group 1 and 1 for Group 2. The results suggested that: (a) both the baseline symptoms and the person mean of NA were significant predictors, B = 0.54, SE = 0.09, t = 6.24, p < .01 for the baseline symptoms; B = 1.58, SE = 0.47, t = 3.38, p < .01 for the person mean of NA; (b) the ALS groups had a non-significant main effect, B = -0.14, SE = 0.58, t = -0.24, p = 0.81; (c) but the ALS groups had a significant interaction with the person mean of NA, B = -1.87, SE = 0.59, t = -3.18, p < .01. To explore this significant interaction (Figure 4), we tested the conditional effect of the person mean of NA for each group (post-hoc simple slope tests:Aiken & West, 1991). The person mean of NA had a higher effect on follow-up depressive symptoms for Group 1, B = 1.58, SE = 0.47, t = 3.38, p < .01, than for Group 2, B = -0.29, SE = 0.38, t = -0.78, p = 0.43. This prospective interaction appears to be unique for depressive symptoms, as we found no such effect on the other measures (i.e., GAD, PSWQ, and PTQ; ps > .05).

Figure 4

Depressive symptoms at the three-month follow-up (PHQ-9 T2) predicted by the person mean of ESM-assessed negative affect



Note. Group 1 (characterized by a bidirectional relationship between repetitive negative thinking and negative affect) experienced higher levels of depressive symptoms if they had higher mean levels of negative affect during the ESM phase. The baseline levels of depressive symptoms were controlled.

Discussion

The results of the ALS clustering replicated the findings of Studies 1 and 2, highlighting the robustness of the two-cluster solution. The clustering identified a consistent pattern of the groupings: i.e., Group 1, characterized by a bidirectional relationship between RNT and NA as well as by increased inertia for both RNT and NA; Group 2, which had smaller auto- and cross-regressive coefficients with only a significant unidirectional effect of NA on RNT (which is more consistent with the results of Study 1 than Study 2). The specific focus of Study 3 was on the prospective effect of the groups on depressive symptoms. We found that the ALS groups are interacted with the person mean of NA to predict the follow-up

levels of depressive symptoms – that is, people who have more rigid and inert dynamics in RNT and NA (so belong to Group 1) and are experiencing higher levels of NA are more likely to develop depressive symptoms to the three-month follow-up. However, we found no significant group differences in the concurrent (or baseline) levels of psychopathology, which replicates Study 2 but is at odds with Study 1. The ALS clustering may, therefore, not be informative to investigate the current symptomatology but may hold a predictive value for future depressive symptoms.

General Discussion

The aim of the current study was to cluster individuals on the basis of the within-person association between RNT and NA (i.e., cross-regressive effects) and their inertia (i.e., auto-regressive effects) that can be captured by ESM. Results of the clustering were replicated across the three studies, showing that typically two groups emerge in non-clinical samples regardless of the differences in the used items and ESM setups. The most consistent finding was that across the three studies, one group was characterized by high levels of inertia and a strong bidirectional association between persistent cognition (RNT or worry) and negative affect.

Previous ESM studies have shown that RNT and NA generally influence each other (e.g., Moberly & Watkins, 2008) and the strength of this RNT-NA association is related to depressive symptoms (Brose et al., 2015). The literature also suggests that emotional inertia is a good predictor of depressive symptoms, both in cross-sectional and prospective studies (Koval et al., 2012; Kuppens et al., 2012).

Our results extend these findings by showing that in the student and general populations, there are systematic and possibly meaningful individual differences in the strength of the RNT-NA associations and their inertia. Importantly, a strong bidirectional

association between RNT and NA is present together with elevated inertia for both RNT and NA in the same group of individuals (cf. rigid responders, Bulteel et al., 2016). These individuals may easily get stuck in a spiral of negative affect and cognition (Koval et al., 2012) as the bidirectionality represents a self-sustaining loop of RNT triggering NA and vice versa; also high inertia means that RNT and NA tend to persist over time. Furthermore, our prospective analysis (in Study 3) revealed that the mean levels of NA that individuals experienced during the ESM phase are another important dimension, interacting with the ALS groups to predict depressive symptoms at the follow-up assessment. This significant interaction may suggest that the triad of high rigidity, high inertia, and high mean levels of negative cognition and affect are key to understanding the psychological etiology of depression.

The current study had an exclusive focus on the within-person dynamics of RNT and NA among non-clinical general and student populations, which were expected to predict future depressive symptoms. Although the results provide preliminary evidence for the predictive values of the RNT-NA dynamics (which may be useful to identify individuals at risk of developing depressive symptoms), caution should be used when generalizing our findings to clinical levels of depression. However, given the continuity between clinical and non-clinical symptomatology, we expect that the dynamics parameters would similarly predict the recurrence of depression in remitted patients and the maintenance of depressive symptoms in currently depressed individuals. Indeed, previous ESM studies suggested that worry becomes more strongly associated with positive and negative affect as a sudden shift in depressive symptoms (or the moment of relapse) approaches (van de Leemput et al., 2014; Wichers, 2014; Wichers et al., 2019). Another study on patients with a history of unipolar depression showed that ruminative inertia is positively associated the with current levels of

depressive symptoms and is negatively associated with the number of past depressive episodes (Bean et al., 2020). However, a direct replication on a clinical sample would be still warranted to establish the clinical relevance of our findings.

The three studies provided somewhat inconsistent results for the concurrent levels of depressive symptoms and other psychopathology variables. In Study 1, the ALS groups significantly differed in depressive symptoms and worry. However, these cross-sectional associations were not replicated in Studies 2 or 3. As noted earlier, we do not regard these inconsistent findings as counter evidence for the predictive value of the ALS clusters. Instead, we speculate that individuals may exhibit high rigidity and high inertia without any depressive symptoms at a given time point, but they are more likely to experience increased levels of depressive symptoms at a later time point than those with low rigidity and inertia. Nevertheless, it is of interest to discuss possible reasons for the inconsistent findings, which may be due to methodological differences between studies. First, the time intervals between ESM signals were not identical across studies (Study 3 used a longer interval than the other two studies). This could have influenced the estimates of RNT-NA associations and inertia as a longer time interval typically results in a lower autoregressive (inertia) effect, which directly or indirectly impacts on the magnitude of the cross-regressive effects (Cole & Maxwell, 2003). There is no uniform solution to determine the optimal time window between ESM signals, and a more systematic investigation is required to find the exact interval with which RNT-NA association becomes the strongest. Second, persistent cognition was operationalized differently across studies. In Study 1, we specifically focused on worry, whereas Studies 2 and 3 used the transdiagnostic construct of RNT. The RNT measure was designed to capture the repetitiveness and persistency of negative thinking as a process. Therefore, the items do not tap into the content of thinking. As worry is characterized as future-oriented thinking, it is

essential to specify the temporal orientation of the thought content in order to assess worry. In future studies, it would be informative to directly compare the results for worry vs. RNT measures, which may help to clarify whether differences in cross-sectional findings across studies were related to differences in conceptualizations of RNT.

Several limitations are noteworthy when interpreting our findings. First, we tested non-clinical samples, and most of them were female university students, which may question the generalizability of our findings. Replication in a wider range of samples (e.g., for the severity of symptoms, gender, and age) is warranted. Nevertheless, recent studies showed that 32% of graduate students are at risk of having or developing a common psychiatric disorder, especially depression (Levecque et al., 2017); therefore, we believe that studying a student or young population is of high clinical relevance. Additionally, we did not collect information about ethnic identification. Second, it is known that the ALS algorithm is not sensitive to small group differences; in other word, it is still possible that there are unidentified (sub)groups (Takano et al., 2020). Unlike Gaussian mixture models, the clustering technique used here (i.e., ALS algorithm) does not assume normality on each regression coefficient estimated through Vector-autoregressive (VAR) models. However, this does not immediately mean that the algorithm is robust for data with outliers. We performed computer simulations to evaluate the accuracy of the ALS algorithm to identify the number of clusters and the cluster allocation of each participant. A typical error of the algorithm was that it overlooked a third cluster when data have three clusters. Given this conservative nature of the algorithm, it is more likely to overlook a potential cluster than to overextract a meaningless cluster (Takano et al., 2020).

Third, we specifically applied the clustering analysis on the bivariate relationship between RNT and NA, which can be, of course, expanded into a greater number of variables

(Bulteel et al., 2016). Such multivariate associations are sometimes understood as a complex psychological network (Epskamp et al., 2016; Pe et al., 2014). Given the recent progress in network psychometrics (Fried, 2020), applying the ALS clustering to a more comprehensive set of cognitive and affective variables would be an interesting direction for future research. Additionally, future studies should examine relation between RNT and positive affect in order to test the specificity of the association between RNT and negative affect. Fourth, we did not have an opportunity to replicate the prospective effect that we found in Study 3. Although this result is quite consistent with the central theories of rumination and depression, a direct or conceptual replication is still appropriate.

Despite these limitations, the current study shows that clustering individuals based on the dynamics in RNT and NA leads to a stable and replicable identification of a group exhibiting high inertia and high rigidity in the association between RNT and NA. Although more research is needed to conclude whether clustering individuals in this way helps identify individuals at risk for psychopathology, this clustering approach has a large potential to identify those who would benefit from preventive intervention targeting the pathological affective and cognitive dynamics.

Study IV: Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Transparency

Authors contribution: T. Ehring developed the study concept and design for Study 1, and T. Ehring, T. Rosenkranz and E. Watkins developed the study concept and design for Studies 2 and 3. Data collection for the Study 2 and 3 was performed by T. Rosenkranz. K. Takano and M. Stefanovic performed the data analysis and interpretation. M. Stefanovic drafted the manuscript and K. Takano, T. Ehring, E. Watkins and T. Rosenkranz provided critical revisions. All authors approved the final version of the manuscript for submission.

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Is A High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Supplementary Online Material (SOM-R)

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Study 1

Table S1

Descriptive Statistics of ESM and Baseline Measures

	All participants		Group 1 (N = 53)		Group 2 (N= 77)		Group difference		
	M	*SD*	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
ESM measures (person means)									
NA	1.31	0.29	1.37	0.31	1.27	0.27	1.83	0.07	0.34
Worry	1.50	0.51	1.66	0.39	1.39	0.38	3.77	< 0.01	0.53
ESM measures (person SDs)									
NA	0.30	0.18	0.34	0.17	0.27	0.18	1.98	0.05	0.40
Worry	0.58	0.32	0.70	0.28	0.50	0.30	3.95	< 0.01	0.69
Baseline measures									
BDI-II	9.10	7.20	10.79	7.96	7.95	6.35	2.17	0.03	0.39
PTQ	27.06	10.23	28.42	9.75	26.13	10.50	1.27	0.20	0.22
STAI-T	40.20	9.89	41.98	10.99	39.57	9.86	1.65	0.10	0.24
PSWQ	49.17	10.74	51.64	9.51	47.47	11.26	2.28	0.02	0.39

Note. NA = Negative Affect; BDI-II = Beck Depression Inventory II; PTQ = Perseverative Thinking Questionnaire; STAI-T= State-Trait Anxiety Inventory Trait; PSWQ = Penn State Worry Questionnaire.

Study 2

Table S2

Descriptive Statistics of ESM and Baseline Measures

	All participants		Group 1 (N = 55)		Group 2 (N= 65)		Group difference		
	M	*SD*	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
ESM measures (person means)									
NA	2.76	0.74	2.76	0.69	2.77	0.79	-0.11	0.90	0.00
RNT	2.13	0.91	2.12	0.83	2.14	0.98	-0.15	0.90	-0.02
ESM measures (person SDs)									
NA	1.01	0.30	1.05	0.30	0.98	0.30	1.35	0.18	0.23
RNT	0.85	0.39	0.92	0.43	0.78	0.34	1.84	0.07	0.23
PHQ-9	5.68	3.73	5.46	2.94	5.86	4.31	-0.59	0.55	-0.12
GAD	5.89	3.44	5.41	3.00	6.30	3.75	-1.43	0.15	-0.26
PSWQ	44.82	10.17	44.91	9.86	44.75	10.51	0.08	0.93	0.01
PTQ	27.65	11.85	27.31	11.60	27.94	12.13	-0.28	0.78	-0.05

Note. NA= Negative Affect; RNT= Repetitive Negative Thinking; PHQ-9= Patient Health Questionnaire; GAD= General Anxiety Disorder; PSWQ= The Penn State Worry Questionnaire; PTQ= Perseverative Thinking Questionnaire

Study 3

Table S3

Descriptive Statistics of ESM, Baseline (T1), and Follow-up (T2) Measures.

	All participants		Group 1 (N=87)		Group 2 (N=99)		Group difference		
	M	*SD*	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
ESM measures (person means)									
NA	2.71	0.71	2.81	0.64	2.63	0.76	1.70	0.09	0.25
RNT	2.01	0.84	2.10	0.82	1.93	0.85	1.40	0.16	0.20
ESM measures (person SDs)									
NA	1.04	0.30	1.08	0.31	1.00	0.29	-1.66	0.10	0.27
RNT	0.80	0.39	0.86	0.43	0.75	0.35	-1.85	0.07	0.28
Baseline measures									
PHQ-9 T1	5.95	3.43	5.77	3.61	6.10	3.27	-0.65	0.51	-0.09
GAD T1	6.28	3.69	6.26	4.05	6.30	3.37	-0.07	0.94	-0.01
PSWQ T1	47.66	10.44	47.70	10.18	47.63	10.72	0.05	0.96	0.01
PTQ T1	28.76	11.51	28.82	11.98	28.71	11.23	-0.06	0.95	0.01
Follow-up measures									
PHQ-9 T2	8.32	4.39	8.41	4.10	8.23	4.65	0.26	0.79	0.04
GAD T2	8.37	3.98	8.73	3.88	8.04	4.06	1.16	0.24	0.17
PSWQ T2	49.09	9.86	49.17	9.48	49.01	10.25	0.11	0.91	0.02
PTQ T2	28.36	11.18	28.79	10.63	27.96	11.71	-0.50	0.62	0.07

Study IV: Is a High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Note. NA= Negative Affect; RNT= Repetitive Negative Thinking; PHQ-9= Patient Health Questionnaire; GAD= General Anxiety Disorder; PSWQ= The Penn State Worry Questionnaire; PTQ= Perseverative Thinking Questionnaire

Is A High Association between Repetitive Negative Thinking and Negative Affect Predictive of Depressive Symptoms? A Clustering Approach for Experience Sampling Data

Supplementary Online Material (SOM-U)

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Study 1

Table S1

Correlations between ESM and Baseline (T1) and Follow-up (T2) Measures.

Variable	1	2	3	4	5	6
1. NA						
2. Worry	.71**					
3. BDI	.41**	.38**				
4. STAI-T	.41**	.40**	.64**			
5. PSWQ	.23**	.30**	.46**	.66**		
6. PTQ	.23**	.30**	.46**	.66**	1.00**	
7. CR	-.12	-.06	-.06	-.04	.01	.01

Note. NA = Negative Affect; BDI-II = Beck Depression Inventory II; PTQ = Perseverative Thinking Questionnaire; STAI-T= State-Trait Anxiety Inventory Trait; PSWQ = Penn State Worry Questionnaire; CR = ESM compliance rate; * indicates $p < .05$. ** indicates $p < .01$.

Study 2

Table S2

Correlations between ESM and Baseline (T1) and Follow-up (T2) Measures.

Variable	1	2	3	4	5
1. NA					
2. RNT	.44**				
3. PHQ-9	.34**	.33**			
4. PTQ	.40**	.38**	.52**		
5. PSWQ	.31**	.31**	.45**	.64**	
6. CR	-.20*	-.08	-.15	-.15	-.01

Note. NA= Negative Affect; RNT= Repetitive Negative Thinking; PHQ-9= Patient Health Questionnaire; GAD= General Anxiety Disorder; PSWQ= The Penn State Worry Questionnaire; PTQ= Perseverative Thinking Questionnaire; CR=ESM compliance rate; * indicates $p < .05$. ** indicates $p < .01$.

Study 3

Table S3

C*orrelations between ESM and Baseline (T1) and Follow-up (T2) Measures.*

Variable	1	2	3	4	5	6	7	8	9	10
1. NA										
2. RNT	.56**									
3. PHQ T1	.26**	.41**								
4. PTQ T1	.25**	.41**	.48**							
5. PSWQ T1	.24**	.40**	.40**	.63**						
6. GAD T1	.36**	.47**	.59**	.51**	.62**					
7. PSWQ T2	.23**	.37**	.37**	.46**	.68**	.44**				
8. GAD T2	.27**	.31**	.39**	.29**	.28**	.38**	.64**			
9. PHQ T2	.22**	.30**	.44**	.29**	.27**	.30**	.60**	.75**		
10. PTQ T2	.24**	.41**	.35**	.55**	.38**	.30**	.63**	.56**	.62**	
11. CR	.00	-.02	.06	-.10	-.01	.05	-.01	.06	.01	-.01

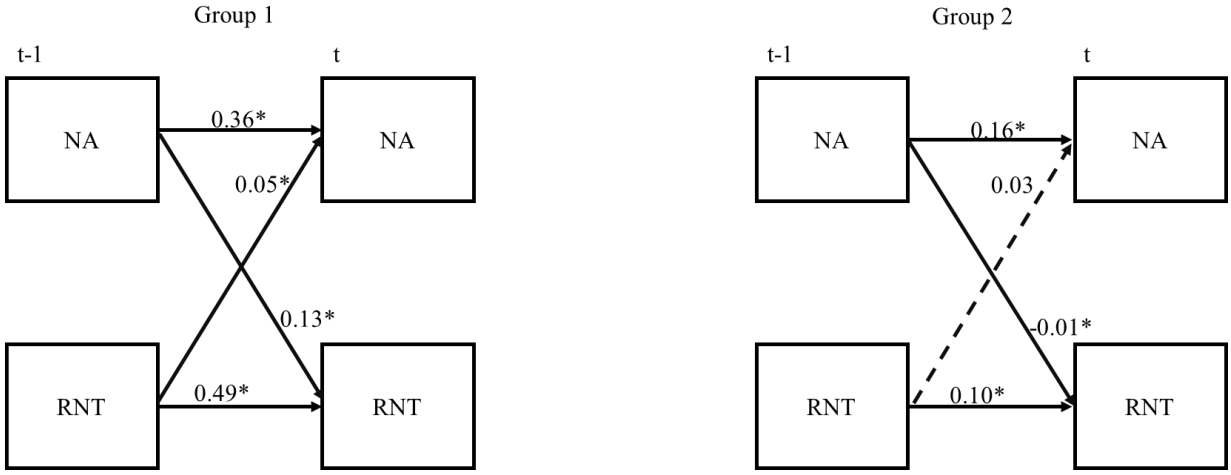
Note. NA= Negative Affect; RNT= Repetitive Negative Thinking; PHQ-9= Patient Health Questionnaire; GAD= General Anxiety Disorder; PSWQ= The Penn State Worry Questionnaire; PTQ= Perseverative Thinking Questionnaire; CR=ESM compliance rate; * indicates $p < .05$. ** indicates $p < .01$.

Sensitivity analysis

In order to test if the relatively high cut-off (= 0.60, Study 3) influences our conclusion, we performed a sensitivity analysis with the cutoff of < 0.40 for Study 3, to be equal as a criteria for Study 1 and 2, which showed that the results were unchanged in terms of the clustering (*Figure S1*) and the prospective effect on depressive symptoms. The multiple regression suggested that both the baseline symptoms and the person mean of NA were significant predictors of depressive symptoms at the follow-up, and that ALS groups had a significant interaction with the person mean of NA, B = -1.83, SE = 0.59, t = -3.10, p < .01.

Figure S1

Groups identified by the ALS algorithm



Note. Group 1 (N = 89) is characterized by higher auto- and cross-regression coefficients than Group 2 (N = 101; the group differences were statistically significant for all regression coefficients). * p < .05, indicating that the coefficient is significantly different from zero.

General Discussion

This dissertation included four empirical studies that overall examined dynamic symptom associations, namely, PTSD symptom associations and associations between RNT and NA.

Study I investigated the influence of the two trauma types on the PTSD symptom dynamic (type I trauma = single event; sudden and unexpected, high levels of acute threat vs. type II trauma = repeated and/or protracted; anticipated). The focus of the second study (**Study II)** was PTSD dynamics within a day, with the twofold goal of investigating which symptoms are most connected with other symptoms within the same moment and which symptoms most predict changes in other symptoms within a few hours across PTSD patients. Symptoms related to trauma related sleep disturbances were excluded from this study, as they corresponded to the sleep disturbances of the previous night and were measured just once in the morning. Therefore, the temporal association between the trauma related sleep disturbances, specifically insomnia symptoms and nightmares, and other PTSD symptoms were the focus of **Study III**. Lastly, as an association between RNT and NA was found to be present in different mental disorders, it was investigated whether it is possible to identify a group of people at risk for depression based on this dynamic (**Study IV**).

In this chapter, the dissertation's main findings are summarized and interpreted. Additionally, general limitations and current challenges are outlined. Finally, implications for future research are discussed.

Summary of Findings

Results of **Study I** indicate that trauma type is a significant moderator of symptom associations in PTSD networks. Network comparison tests provided strong evidence that networks between two trauma types differ globally. Furthermore, specific edges that differ were identified. The distinction between the two large groups of traumatic experiences was

broad. However, it is important to note that the grouping underlying the analyses was based on theoretical and empirical findings on the distinction between repeated vs. single-event trauma. Previous studies revealed that there is strong evidence showing that sudden and unexpected traumatic events that are characterized by high levels of acute threat (e.g., accidents; single episodes of physical or sexual assault) may lead to different symptom presentations than repeated and/or protracted traumatic events, especially those that are experienced early in life (e.g., sexual and/or physical maltreatment in childhood) (Cloitre et al., 2013; Courtois & Ford, 2009). This study extended previous findings and showed that trauma type, namely certain characteristics of the traumatic events, indeed influence associations between symptoms. The relevance of those findings should be further explored in treatment studies, which should test whether different symptom constellations influence treatment outcomes as well. Even though the two categories used in the current study had overlaps of the type of traumatic events (e.g., sexual trauma is included in both categories), they could be distinguished by whether these traumatic events were repeated or single events, which is a crucial distinction. Using two trauma types, based on categories that are grounded in the theoretical and empirical literature, differences in symptom constellations were indeed found. To date, PTSD network literature has provided some inconsistent findings. Therefore, current findings indicate that it is important to consider trauma type, as well as specific characteristics of the traumatic events, as an important moderator. Furthermore, since Study I investigated between-person associations, **Study II** additionally investigated within-person associations, namely dynamic PTSD network models. The results revealed that PTSD symptoms are differently connected within the same moment (*contemporaneous* network) and within the next few hours (*temporal* network). The temporal network comprised more negative associations, meaning that increases in certain symptoms led to decreases in other

symptoms within a few hours and vice versa. In contrast to *temporal* networks, in *contemporaneous* networks, symptoms showed stronger synchronization with only few negative associations. Those findings form the hypotheses that symptoms are probably activated at the same moment, but within a few hours, they have begun regulating each other and persist due to the interrelated influence. Those assumptions should be further investigated to determine whether there is a mutual trigger for the appearance of symptoms, which could explain more positive correlations within the *contemporaneous* network, whereas in the *temporal* network, it must be determined whether certain symptoms are causing an increase or a decrease of the other symptoms. Differences between *contemporaneous* and *temporal* networks illustrate that PTSD dynamics differ even within hours. *Difficulty staying emotionally close to other people* had the most connections with other symptom within the *contemporaneous* network, while *hypervigilance* predicted the changes in most other symptoms in the *temporal* network. Temporal networks provide insight into the hypotheses regarding causality but indeed those findings have to be directly tested using designs that more directly manipulate variables.

Study III complemented the findings of the PTSD symptom dynamics by focusing on the role of trauma related sleep disturbances – insomnia symptoms and nightmares – on other PTSD symptoms. Results showed that insomnia and nightmares significantly predicted PTSD symptoms on the following day, but that this effect is unidirectional, since PTSD symptoms did not predict insomnia symptoms or nightmares on the following night. Additionally, further analysis revealed that nightmares mediate the relationship between insomnia symptoms and PTSD symptoms on the following day. Those findings indicate that trauma related sleep disturbances play a significant role in the maintenance of PTSD and they are important to consider in planning treatment.

In conclusion, the results of Study I indicate that trauma type moderates PTSD symptom dynamics. Those findings led to a question about what other moderators influence symptom dynamics and potentially explain inconsistent findings in the PTSD network literature to date. There are symptom associations that are repeatedly found on the between- and within-subject levels (Study I & Study II). Those findings contribute to the idea that some symptom associations are core for PTSD and could repeatedly be found across different analysis levels and across different study populations. If specific characteristics of the traumatic event act as moderators to influence PTSD symptom dynamics, this leads to the question of what other possible moderators are and what influence they have. Would it be enough to further explore possible moderators and control their influence or to shift the research in the direction of idiographic network models?

Finally, associations between NA and RNT have been found to be present in different mental disorders, so predictive values of this dynamic were further explored. Using a clustering algorithm, two groups of individuals in non-clinical samples were repeatedly identified, across three different ESM data sets in **Study IV**. The first group was characterized by a higher bidirectional association between RNT and NA (and also greater inertia) than the other group. Further analysis showed that by using the momentary assessment of RNT and NA, it was possible to identify individuals at risk of depression. The Predictive value of this specific association, also considered to be a transdiagnostic risk factor, could be used to identify individuals at risk who would benefit from preventive interventions.

PTSD is also associated with NA (DiMauro et al., 2016) and rumination (Hetelekides et al., 2022), and the clustering potential, based on this association, could be further explored across PTSD patients. As this dynamic was examined in a young population, it would be meaningful to replicate those findings on a clinical sample. It is expected that this association

would have important predictive value on a clinical sample as a recent study has shown that PTSD was significantly associated with rumination and mental health outcomes, and that this was stronger across a military sample than across a student sample (Hetelekides et al., 2022).

General Limitations & Challenges

There are several methodological limitations and challenges related to this dissertation and the research focus in general, so it is to consider these.

First, associations found in within-subject models (**Studies II, III** and **IV**) as well as in between-subjects models (**Study I**) could be influenced by a third-variable, known as *Simpson's paradox*. Research show that this paradox will appear when conclusions are drawn across different research levels (e.g., from populations to subgroups; from subgroups to individuals) (Kievit et al., 2013). This issue can be resolved when confounding variables and causal relations are appropriately addressed in the statistical modelling. However, even if we control for some already known moderators (e.g., gender, education, trauma type), it is still challenging to list all the possible confounding variables and predict and control external influences.

Second, as researchers use different inclusion criteria when choosing a study population, it is important to consider *Berkson's paradox* (Berkson, 1946). Often, if we are interested in the symptom network of a specific disorder, we aim to include individuals who satisfied criteria for the diagnosis of the disorder of interest (McNally, 2021). This sounds intuitively logical. However, this could be problematic due to Berkson's paradox and this limitation is not restricted merely to the network analysis, but any network analysis is not resistant to this paradox (McNally, 2021). This paradox can be illustrated by a simple example. If the goal is to predict whether knowledge of a language is a significant predictor of the ability to understand a text written in that same language, and if the analysis is limited just

to native speakers of the chosen language, then language knowledge, despite being crucial to understanding a text, will not be a significant predictor, as it doesn't significantly vary between individuals (if it is assumed that all native speakers have sufficient knowledge to understand a basic text written in the native language). However, if non-native speakers are included in the analysis, along with individuals who do not understand the language in which the text is written, the knowledge level of the specific language will definitely be a significant predictor of successful understanding of a text. The same principle applies to different diagnoses: inclusion criteria will indeed influence the results and result in *Berkson's paradox* if nodes are closely related with the inclusion criteria (McNally, 2021). This issue could be addressed by including samples with bigger variability, e.g., individuals with different symptom severity or additional comorbid disorders, and then controlling for possible confounding variables in the analysis. Specifically, for PTSD patients it is important to consider variables, such as depression, anxiety, and substance use symptoms.

Third, it is important to include variables from the *external field* (a term borrowed from physics) to illustrate external influences on the individual in networks and to find the best approach to studying associations between symptoms and those external factors, because these symptoms will naturally cluster together and have closer relationships with each other (Isvoranu, 2021). There is no unique solution to determining what are the most relevant variables from the external field to include in a network model and whether is possible to identify variables that are common across different subgroups (e.g., different trauma types, clinical population, traumatized population). Furthermore, in addition to psychological variables and external field variables, it is important to consider biological variables (e.g., cortisol level, heart rate, actigraphy). There is an open question about whether different variables (e.g., psychological variables, external influences, biological variables) should be

studied in the same network model (Fried & Cramer, 2017) or whether they should be simultaneously investigated but in separate networks (Blanken et al., 2021).

Fourth, related to the idea of the external field, it is important to acknowledge that mental disorders emerge in a person's daily life and to consider environment as an important part of the system (Olthof et al., 2020). However, even though the ESM approach was used, and data collection took 15 days (Study II and Study III) and 4, 14, and 10 days respectively (Study IV), it is possible that important events were missed. Additionally, part of the sample was in inpatient treatment (Study II and Study III). Inpatient centres, namely the hospital environment, is not a typical representation of individual daily life because external influences were limited and/or different than usual, which must be taken into consideration. Additionally, part of the data collection (Study II and Study III) took place during the COVID-19 pandemic, which also influenced the participants' daily lives.

Fifth, by using the ESM approach, we can investigate symptom dynamics in people's daily lives, yet there are important variables to consider that do not fluctuate within-person on a daily level, such as different risk and protective factors, negative events, ethnicity, and childhood trauma (Isvoranu, 2021). It is important to include these variables in the model. Similarly, there are symptoms that can last longer and occur when person are not able to respond to the questionnaires (e.g., during the dissociative phase), and, conversely, there are "*fast*" changes, e.g., flashbacks, that last just a few seconds. It is challenging to incorporate assessments of these "s*low*" and "*fast*" dynamics (Olthof et al., 2020).

Sixth, items typically used in the ESM assessment are adapted from questionnaires that were validated on the between-person level. A recent study by Brose et al. (2020) showed disadvantages of this practise because psychometric properties differ across the between-person and within-person levels.

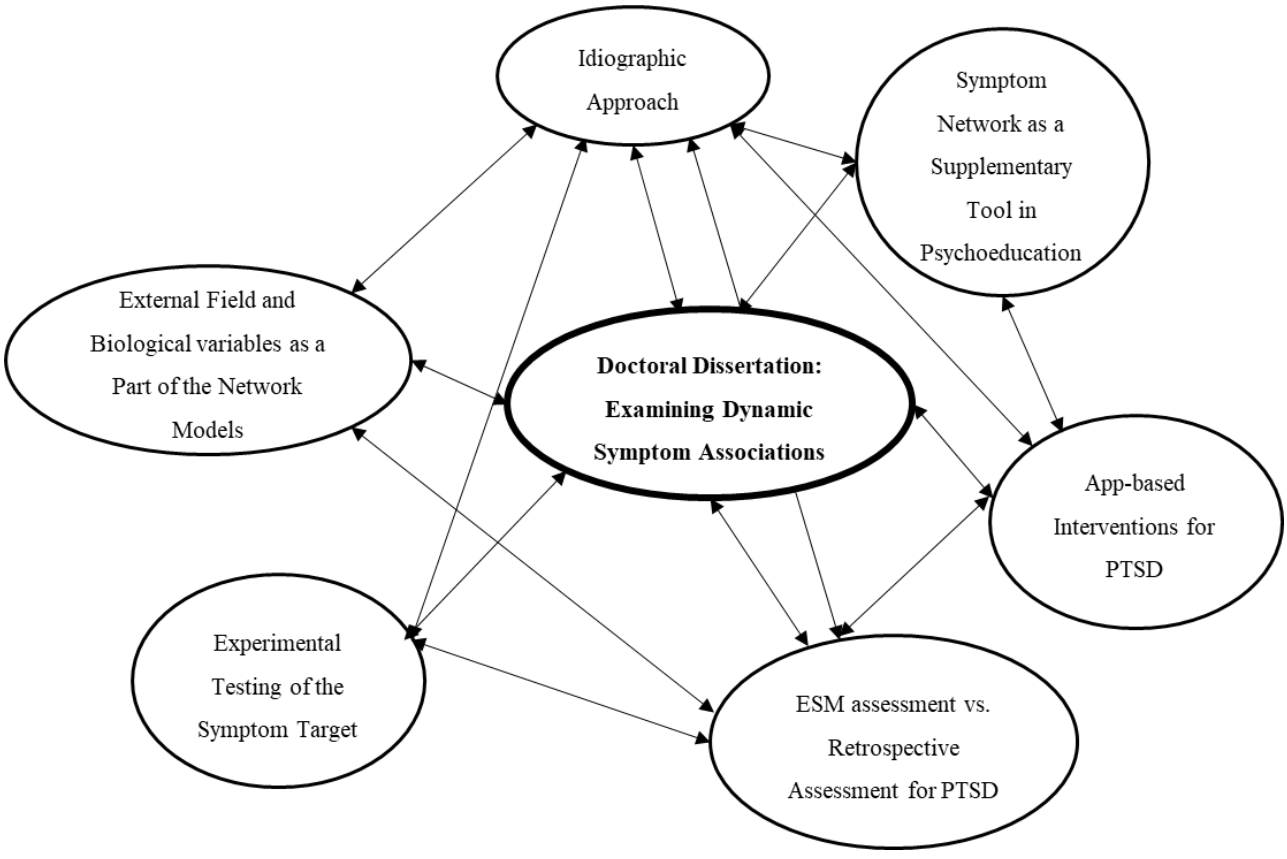
Lastly, even though the ESM approach has a lot of advantages, it is important to consider that repeated reporting of symptoms is already an intervention that should be taken into consideration.

Implications for Future Research

Based on the findings of this dissertation and the limitations and challenges outlined above, future research should address the following issues (please see *Figure 1*). Although it is not possible to clearly distinguish between methodological and practical implications, as they are naturally interrelated, for a better overview, the implications for the future research are divided into two categories: implications for future research related to the methodology and implications related to clinical practise.

Figure 1

Directions for future research using this dissertation as a central point



Methodological Implications

Some of the identified challenges, such as *Simpson's paradox*, which appears when conclusions are generalized from subgroups to individuals (Kievit et al., 2013), could be addressed by using personalized networks. The use of personalized networks could avoid the potential danger of generalizing findings found on a subgroup level to a single individual. Considering that previous findings have demonstrated that there are *636,120 ways* to have PTSD (Galatzer-Levy & Bryant, 2013), due to the numerous symptom combinations, it is indeed important to investigate whether there are significant individual differences in the PTSD network models, namely symptom constellations, and whether this is an important factor to consider. However, there is also an additional question: could we, beginning with individualized networks, recognize a pattern that is still common for specific subgroups using a clustering algorithm (as applied in Study IV)?

Future research should investigate systematic differences between an ESM assessment vs. traditional retrospective assessments of PTSD. How much information do we miss by assessing symptoms retrospectively for the last weeks or month, and does this "missed" information really matter? Can we improve the psychotherapy for PTSD with detailed ESM assessments or are we just exposing patients to unnecessary daily (hourly) burdens? What it the appropriate ESM setting for PTSD patients, and how many times per day for how many days in a row it is necessary to assess PTSD symptoms? Additionally, it is essential to develop items specifically for an ESM assessment and to validate it on the within-person level.

As discussed above, *reductionism*, namely investigation of an isolated phenomena, is not very informative if we consider mental disorders as a complex system. In addition to the psychological variables, network models should include the external field and biological

variables. The jury is still out on whether those variables should be studied in one model or in separate models in parallel. Indeed, this is emerging question that future studies should address: which variables, in addition to the symptoms, should be included in the network and how should those interrelations be studied?

Practical Recommendations

The first question, which has emerged in the recent symptom network literature, is to test whether by targeting the symptoms with the strongest centrality / out-strength it is possible to reduce other symptoms. However, it is challenging to target specific symptoms without simultaneously influencing other ones (Bringmann et al., 2022; Eronen, 2020; McNally, 2021). In order to answer this question of causality, experimental studies are needed. Future studies should directly manipulate specific symptoms and test causality.

Additionally, study IV showed that based on the specific symptom associations is possible to identify people of risk for psychopathology. After estimating the network presentation and identifying core edges for specific disorder, including PTSD, clustering algorithm used in the Study IV could be further applied to identify specific group of individuals based on the core edges and examine whether this core edges could be used as an predictive indicator for the unsuccessful treatment or drop out.

Furthermore, according to the cognitive model of PTSD by Ehlers & Clark, being aware of and identifying triggers is an intervention (Ehlers & Clark, 2000). Could we decrease PTSD symptoms by using the app-based interventions, in which patients will be instructed to report their triggers and describe the differences between the traumatic event and the present-day triggers, namely discrimination training to identify “then” vs. “now”? According to a report from the World Health Organisation (WHO), in many countries

worldwide, there is fewer than 1 psychologist[8] working in the mental health sector per 100,000 inhabitants (World Health Organization, 2019). On the other hand, according to Statista, 83.96% of the world's population owns a smartphone and this number is expected to increase in the coming years (Statista, 2021). If app-based interventions, specifically identification of triggers and discriminative training for PTSD patients, can improve the symptomatology, we could balance the numbers of available psychotherapists vs. smartphones and use app-based interventions as an alternative strategy. Even though app-based interventions cannot replace the psychotherapy treatment, they could be used as an alternative for those who do not have access to mental health care or as a bridging strategy for those who face long waiting lists for treatment. A self-help app could contain different phases (please see *Figure 2*). In the first step, patients would answer questions related to their current symptomatology. Based on their answers, in a second step, patients would receive feedback about their symptom severity. Additionally, network presentations could be estimated and used as a supplementary tool for the psycho education part. Network presentations could be used as part of psychotherapy treatment, where therapists could discuss possible symptom associations and the symptom flow with the patients. This could help patients to understand the development of the disorder and to develop a potential hypothesis together with the therapist. Additionally, a patient's personal experience could help understand the symptom's development, e.g., by providing additional information about their daily life. Research has shown that feedback increases treatment motivation (Musiat et al., 2012) and that visual presentation is a powerful learning tool (Bobek & Tversky, 2016).

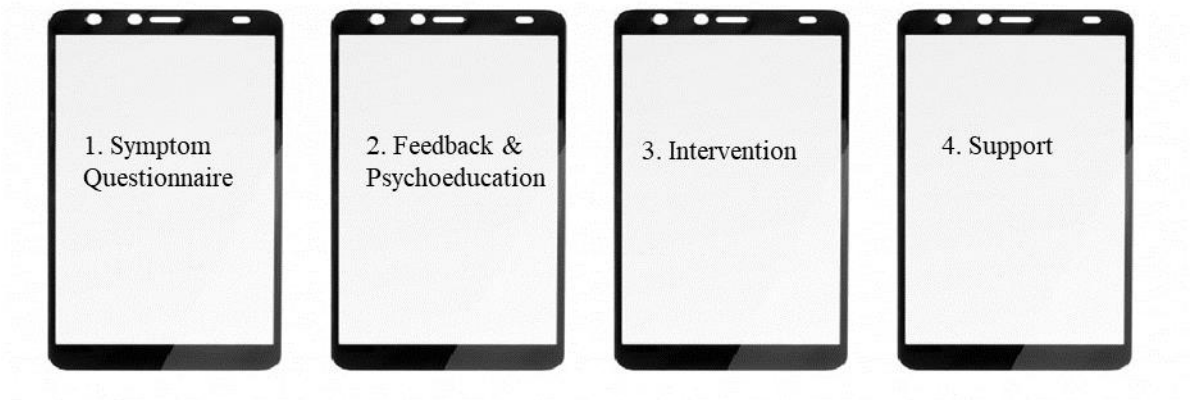
In the next step, patients could be offered different interventions, such as discriminative training in which patients list their triggers, which is already an intervention

[8] There were no available data about psychotherapists worldwide, but as psychology studies are required for psychotherapy licences in many countries, it is estimated that the number of psychotherapists is actually smaller and the number of trauma specialized psychotherapists is subsequently even smaller.

(Ehlers & Clark, 2000), and patients could compare similarities and differences between the traumatic events and events that actually trigger them. Furthermore, imaginary rescripting (Arntz, 2012), an intervention that addresses specific memories of earlier traumatic experiences, could be adapted for digital use and gamified. Namely, typical traumatic events could be presented as a that patients could choose to "play". Patients could personalize the game and have an opportunity to add details that would remind them of the traumatic situation (e.g., create the people, environment, and weather, or add different sounds or lights) and have a chance to react to the gamified situation. A patient could, for example, dress a perpetrator in ridiculous clothing that would make the patient laugh, or to the patient could finish the "game" with an alternate outcome that would make the patient feel better. In this way, patients would be confronted with the traumatic situation, but in a safe environment. At the end of each intervention, patients should again fill out questionnaires related to their symptoms and mood, and they should have a support option so that they can always find contact information in the case of crisis. These interventions should be studied in randomized controlled trials. If studies prove the success of such interventions, this could lead to the *prescribed app*.

Figure 2

Example of the different phases of the app



Conclusion

The focus of this dissertation was examination of the dynamic symptom associations in cases of posttraumatic stress disorder and repetitive negative thinking. Overall, four studies were included and provided the following conclusions.

First, trauma type is an important moderator in PTSD symptom networks; namely, specific characteristics of traumatic events influence symptom constellations in PTSD symptom networks. Second, *contemporaneous* and *temporal* PTSD networks differ and it is important to estimate both types of network. Additionally, in the temporal PTSD network of PTSD patients, *hypervigilance* predicts changes in the greatest amount of other symptoms that could be important to consider in planning treatment. Third, analysis has revealed that trauma-related sleep disturbances, including insomnia symptoms and nightmares, play an important role in the maintenance of PTSD on the following day. Lastly, based on the dynamic association between RNT and NA, it is possible to identify individuals at risk of depressive symptomatology.

This dissertation has answered important questions but it has also opened up new questions that future research will need to address, with the most important goal being to improve diagnostics, treatment, and, most importantly, the well-being of the individual. Results obtained in this dissertation could be further extended by including knowledge from psychology, biology, statistics, mathematics, app programming, and art. Indeed, future research should combine expertise from different fields and move in the direction of multidisciplinary research.

Zusammenfassung

Untersuchung von Symptomzusammenhängen im zeitlichen Verlauf anhand Posttraumatischer Belastungsstörung und Repetitivem Negativem Denken

In letzter Zeit haben Netzwerkanalysen als neuartiger Ansatz zur Konzeptualisierung von psychischen Störungen verstärkt Eingang in die Forschung gefunden (Borsboom & Cramer, 2013). Darunter sind statistische Verfahren zu verstehen, welche zur Untersuchung und Visualisierung bestimmter Phänomene und deren Zusammenhänge in Form von Korrelationen herangezogen werden. Ziel dabei ist, konditionale Abhängigkeitsstrukturen in Form von Netzwerken abzubilden, wobei die Knoten (engl. *nodes*) als die jeweiligen Entitäten mitsamt den jeweiligen Assoziationen repräsentiert werden.

Die vorliegende Dissertation beschäftigt sich mit Netzwerken psychologischer Variablen, genauer Symptomen der Posttraumatischen Belastungsstörung (PTBS). Solche Variablen (z.B. Symptome, Stimmung, Eigenschaften) werden innerhalb der Netzwerke als *nodes*, die Assoziationen zwischen ihnen als *edges* bezeichnet (Epskamp, 2017). Letztere können auf unterschiedliche Weise, z.B. durch unterschiedliche Farben und Stärken, visualisiert werden, wobei grüne/blaue Farben meist positive und rote Farben meist negative Korrelationen darstellen. *Edges* zeigen nicht nur die direkten Verbindungen zwischen den *nodes* bzw. Variablen an, sondern auch deren Stärke (visualisiert durch breite bzw. schmale Linien). Darüber hinaus kann zwischen gerichteten Assoziationen (*edges* mit Pfeilspitze) und ungerichteten bzw. wechselseitigen Assoziationen (*edges* ohne Pfeilspitze) unterschieden werden. Psychologische Netzwerke, die anhand von Querschnittsdaten geschätzt werden, sind typischerweise ungerichtet, während Netzwerke basierend auf Längsschnitt- oder Zeitreihendaten typischerweise gerichtet sind (Epskamp, 2017).

Entsprechend netzwerk-theoretischer Überlegungen spielen Symptome und deren Wechselwirkungen eine zentrale Rolle in der Entwicklung und Aufrechterhaltung von psychischen Störungen. Sie spiegeln dabei theoretische Konzepte der kognitiven Verhaltenstherapie wider, wonach Psychopathologien als Konsequenzen wechselseitiger

Bedingungen von Kognitionen, Emotionen und Verhalten zu Tage treten (e.g., Beck, 1967). Es wird zudem postuliert, dass der Netzwerk-Ansatz in der Lage ist, das Auftreten bestimmter Symptome innerhalb von Störungsbildern wie auch über unterschiedliche Störungsbilder hinweg zu erklären. Der Ansatz kann somit helfen, verschiedene Kernsymptome, die eine bestimmte Störung wie z.B. die post-traumatische Belastungsstörung ausmachen, und deren gegenseitige Abhängigkeiten zu charakterisieren.

PTBS wurde erstmalig im Jahr 1980 in das Diagnose- und Klassifikationssystem DSM (Diagnostic and Statistic Manual of Mental Disorders; DSM-III: American Psychiatric Association, 1980) aufgenommen. Die Nützlichkeit und Validität dieser Diagnose wurde seitdem weithin anerkannt. Dennoch gab es jahrzehntelange Diskussionen über die genaue Formulierung der Diagnosekriterien, wobei diese Debatte weiterhin anhält. Die erste Frage betrifft dabei die Heterogenität in der Anzahl und Arten von Symptomen, welche in die Diagnosekriterien mitaufgenommen werden sollten (Hansen et al., 2015; Hyland et al., 2016; O'Donnell et al., 2014). Der zweite Punkt dreht sich vornehmlich um die Frage, ob es eine einheitliche Definition für PTBS geben sollte, oder ob einfache vs. komplexe Symptomdarbietungen als verschiedene Störungen konzeptualisiert werden sollten. Mit jeder Revision des DSM erfolgte auch eine Änderung der Diagnosekriterien für PTBS, welche die anhaltendende Debatte um kontroverse Punkte reflektierte.

Die jüngsten Versionen der beiden großen Diagnosesysteme, die fünfte Version des DSM (DSM-5; American Psychiatric Association, 2013) und die elfte Version der Internationalen Statistischen Klassifikation der Krankheiten (ICD-11; World Health Organization, 2021) schlagen recht unterschiedliche Ansätze zur Diagnostik einer PTBS vor. Das DSM-5 nennt eine allgemeine Diagnose, die insgesamt 20 verschiedene, in vier Cluster aufgeteilte Symptome umfasst. Diese Symptome können in sehr unterschiedlichen

Kombinationen und Konstellationen auftreten (Galatzer-Levy & Bryant, 2013) und Überlappungen mit anderen Störungsbildern beinhalten (Mitchell et al., 2017). Die neu vorgeschlagenen PTBS-Kriterien der ICD-11 hingegen umfassen nur sechs Symptome einer „einfachen“ PTBS (World Health Organization, 2021). Zusätzlich führt die ICD-11 führt jedoch eine separate diagnostische Kategorie für die „komplexe“ PTBS ein, die drei Kernelemente umfasst: anhaltende Störungen in den Bereichen Affekt, Selbstkonzept und zwischenmenschliche Beziehungen (World Health Organization, 2021). Welcher Ansatz aus praktischer und theoretischer Sicht valider und nützlicher ist, ist noch nicht endgültig geklärt.

In den letzten zehn Jahren spielte die Netzwerkperspektive in der klinisch-psychologischen Forschung eine zunehmend wichtige Rolle. Konzeptionell wurde sie erstmals 2008 untersucht (Borsboom, 2008) und zwei Jahre später erstmals empirisch überprüft (Cramer et al., 2010). Weitere fünf Jahre später erschienen die ersten Veröffentlichungen zum Netzwerkansatz im Bereich posttraumatischer Stressforschung (McNally et al., 2015; Schryver et al., 2015). Seitdem ist die Zahl der Studien, welche PTBS aus Netzwerkperspektive betrachten, deutlich angestiegen, und in der neuesten Metaanalyse konnten bereits mehr als 70 Studien gezählt werden (für detaillierte Informationen zu den Studien: Isvoranu et al., 2021).

Querschnittliche PTBS-Netzwerke wurden bisher für verschiedene Populationen geschätzt. Darunter sind Studien mit nicht-klinischen Populationen (Armour et al., 2020; Benfer et al., 2018; Eddinger et al., 2020), Flüchtlingen (Pfeiffer et al., 2019; Spiller et al., 2017), kriegsbetroffenen Jugendlichen (Schryver et al., 2015), Überlebenden von Naturkatastrophen (Ge et al., 2019; McNally et al., 2015; Russell et al, 2017) sowie Terroranschlägen (Birkeland & Heir, 2017), Militärveteranen (Armour et al., 2017; Lazarov et al., 2019; Mitchell et al., 2017; Moshier et al., 2018; Phillips et al., 2018; Simons et al., 2019;

Stockert et al, 2018), erwachsenen Überlebenden von Kindesmissbrauch (Knefel et al., 2016; McNally et al., 2017), behandlungssuchenden Patienten (Djelantik et al., 2020; Fried et al., 2018) sowie Patienten, die traumatischen Ereignissen ausgesetzt waren (Park et al., 2019).

In einer kürzlich durchgeführten systematischen Übersichtsarbeit sowie einer Metaanalyse konnten einige *edges* identifiziert werden, die sich als robust über verschiedene Stichproben hinweg erwiesen: *Hypervigilanz* und *Schreckhaftigkeit*, *Alpträume* und *intrusive Gedanken*, *internale* und *externale Vermeidung*, *emotionale Taubheit* und *das Gefühl der Abgetrenntheit*; *das Gefühl der Abgetrenntheit*, *Interessenverlust* und *Amnesie* stellten dabei die Symptome dar, die am *wenigsten* zentral waren (Birkeland et al., 2020; Fried et al., 2018; Isvoranu et al., 2021). Das Hauptergebnis der Meta-Analyse zeigte jedoch, dass es kein spezifisches Symptom gibt, welches sich als über verschiedene Populationen hinweg als zentral erweist (Isvoranu et al., 2021). Trotz einiger robuster Befunde sind die Ergebnisse der verschiedenen Studien zum PTBS-Netzwerk immer noch widersprüchlich, wobei die Frage nach dem Grund für diese divergierenden Befunde bisher unbeantwortet bleibt. Während sich die Vielzahl der veröffentlichten Studien auf die Schätzung sog. *contemporaneous networks* beziehen, bei der die partiellen Korrelationen zwischen Symptomen *innerhalb desselben Messzeitpunkts* veranschaulicht werden, untersuchen Studien zu sog. *temporal networks*, wie sich Symptome gegenseitig *zum nächsten Messzeitpunkt* beeinflussen (Greene et al., 2018; Hoffart et al., 2019; Price et al., 2020; Reeves & Fisher, 2020). Hierzu ist die Studienanzahl deutlich geringer.

Parallel zur Studienlage bei *contemporaneous networks* findet sich auch bei Studien zu *temporal networks* eine große Heterogenität bezüglich der untersuchten Stichprobe. Verschiedenen Studien untersuchten israelische Zivilisten, die Raketenangriffe miterlebt hatten (Greene et al., 2018), traumatisierte Personen in einer akuten Post-Traumaphase (Price

et al., 2020), Patienten mit PTBS, die an einer Expositionstherapie teilnahmen (Hoffart et al., 2019), und eine gemischten Gruppe von Personen, die die Kriterien für eine PTBS erfüllten (Reeves & Fisher, 2020).

In Anbetracht der bisherigen Ergebnisse der PTBS-Netzwerkstudien und Netzwerkstudien im Allgemeinen gibt es einige Herausforderungen, denen in dieser Arbeit begegnet wurde. Erstens wurden bislang zwar eine Vielzahl von Studien zu *contemporaneous networks* bei PTBS veröffentlicht, jedoch gibt es immer noch einige widersprüchliche Ergebnisse. Zweitens ist es notwendig, Rückschaufehler zu vermeiden und PTBS Symptome im Alltag der Personen mithilfe der „Experience Sampling Method“ (ESM) zu untersuchen. Die ESM ist ein wichtiges Erhebungsinstrument (z.B. durch täglich mehrmalige Erhebungen über ein Smartphone), das Forschern und Klinikern hilft, durch mehrfache Erhebungen über die Zeit Einblick in verschiedene, individuelle Abläufe im Alltag einer Person zu erlangen (Trull & Ebner-Priemer, 2013). Der größte Vorteil des ESM-Ansatzes ist die dabei die ökologische Validität, welche durch die Erhebungen im Alltag der Probanden erreicht wird. Die Daten werden dabei üblicherweise mehrmals am Tag erhoben, was präzise, detaillierte Informationen und die Möglichkeit zur Untersuchung der Variabilität von Erfahrungen ermöglicht. Viertens wäre es sehr wichtig zu untersuchen, ob es möglich ist, auf der Grundlage spezifischer Assoziationen (z.B. repetitives negatives Denken und negativer Affekt, die bei vielen verschiedenen Störungenvorkommen) Personen mit einem erhöhten Depressionsrisiko erkennen zu können.

Diese Dissertation umfasst vier empirische Studien, die sich den oben genannten Herausforderungen angenommen haben.

Studie I untersuchte den differenziellen Einfluss der beiden Traumatypen (Typ I Trauma = einmaliges Ereignis; plötzlich und unerwartet, hohes Maß an akuter Bedrohung vs.

Typ II Trauma = wiederholt und/oderlänger anhaltend; erwartet) auf Symptomnetzwerke, da frühere Studien bereits einen signifikanten Einfluss auf Symptomassoziation, PTBS Prävalenz (Cloitre et al., 2009; Kelley et al., 2009; Kilpatrick et al., 2013; Shevlin & Elklit, 2012; Stein et al., 2016) und Symptomschwere (Cloitre et al., 2009; Cloitre et al., 2013) zeigen konnten. Ziel der Studie I war es, die bisherige Evidenz zu erweitern und zu prüfen, ob die Art des Traumatyps die Symptomkonstellation in querschnittlichen Netzwerkanalysen zu PTBS beeinflusst. Die Unterscheidung zwischen Typ-I und Typ-II-Trauma könnte dabei eine mögliche Erklärung für die widersprüchlichen Ergebnisse in bisheriger Forschung zu diesem Themenbereich liefern. Bei den Probanden der Studie I handelte es sich um traumatisierte Personen mit erhöhter PTBS-Symptomatik. Der Großteil (94%) befand sich zum Zeitpunkt der Studie in der Diagnostikphase zur Aufnahme einer PTBS-Behandlung in unterschiedlichen Zentren in Deutschland und der Schweiz (*n* = 286 mit Trauma Typ I und *n* = 187 mit Trauma Typ II). Für jede der beiden Gruppen wurde ein *Bayesian Gaussian graphical model* geschätzt und die Gruppenunterschiede in den Symptomnetzwerken untersucht. Die Analysen zeigten erstens, dass für beide Traumatypen die identifizierten *edges* früherer Netzwerkanalysen repliziert werden konnten. Zweitens konnten gesicherte Belege dafür gefunden werden, dass die Netzwerke beider Traumatypen aus unterschiedlichen multivariaten Normalverteilungen generiert wurden, d.h. sich die Netzwerke auf globaler Ebene voneinander unterschieden. Drittens ergaben explorative Vergleiche der *edges* einen moderaten bis starken Hinweis auf auf für den jeweiligen Traumatyp spezifischen *edges*. Unsere Ergebnisse weisen darauf hin, dass der Traumatyp zur Heterogenität des Symptomnetzwerks beiträgt. Zukünftige Forschung zu Symptomnetzwerken bei PTBS sollten daher diese Variable in ihren Analysen berücksichtigen, um die Heterogenität zu reduzieren.

Die zweite Studie (**Studie II**) beschäftigte sich mit der Dynamik von PTBS-Symptomen innerhalb eines Tages bei PTBS-Patienten. Ein besonderer Fokus lag hierbei auf Symptomen mit hoher Vorhersagekraft zur Veränderung anderer relevanter Symptome. Die Studie beinhaltete ein Baseline-Datenerfassung, gefolgt von einer Smartphone-basierten ESM-Messung. Die Probanden beantworteten an 15 aufeinanderfolgenden Tagen viermal am Tag Fragen zur Erfassung von PTBS Symptomen. Die Rekrutierung der Probanden erfolgte in verschiedenen stationären und ambulanten Zentren mit Behandlungsschwerpunkt Trauma in München, Deutschland. Die Stichprobe umfasste 48 Personen, die nach einer Behandlung gesucht, jedoch noch keine trauma-fokussierte Behandlung begonnen hatten. Bei 44 der Probanden war PTBS die primäre Diagnose, 4 Probanden zeigten ein subsyndromales Störungsbild der PTBS. Die ESM-Erhebung beinhaltete 20 Items der PTSD Checklist for DSM-5 (PCL-5), fünf Items des International Trauma Questionnaire (ITQ) zur Erfassung von Beeinträchtigungen in der Beziehungsgestaltung und der Funktionalität, und zwei Items der Clinician-Administered PTSD Scale for DSM-5 (CAPS) zur Erfassung von Derealisations- und Depersonalisationssymptomatik. Das *contemporaneous* and *temporal* Netzwerk unterschieden sich dabei deutlich voneinander. Das *temporal network* zeigte, dass Veränderungen in der *Hypervigilanz* Veränderungen der meisten übrigen Symptome zum nächsten Messzeitpunkt vorhersagten. Darüber hinaus zeigte *Hypervigilanz* temporäre Verbindungen zu mindestens einem Symptom jedes DSM-5 Symptomclusters. *Hypervigilanz* sagt bei PTBS-Patient:innen folglich das Auftreten vieler Symptome prospektiv vorher. Hypervigilanz sollte möglicherweise daher bei der traumafokussierten Behandlung von PTBS verstärkt in Betracht gezogen wegen. Diese Schlussfolgerung steht jedoch unter dem Vorbehalt weiterer Forschung, welche diesen Ansatzpunkt empirisch untermauern kann.

Die dritte Studie (**Studie III**) fokussierte sich auf die Rolle trauma-assoziierter Schlafstörungen: Insomnie und Alpträume. Hierzu wurden zeitliche Zusammenhänge zwischen schlafbezogenen Items and PTBS-Symptomen betrachtet. Es liegen bereits robuste Befunde für den Einfluss von Schlafstörungen bei der Aufrechterhaltung von PTBS vor. Jedoch fehlt es an Wissen über Veränderungen trauma-assoziierter Schlafstörungen Insomnie und Alpträume, von Tag zu Tag und ihres Zusammenhangs mit PTBS-Symptomatik. Deshalb untersuchten wir ihr dynamisches Wechselspiel im Alltag mittels ESM. Es wurde dieselbe Stichprobe wie für Studie II herangezogen. Mehrebenenanalysen zeigten, dass Insomnie und Alpträume signifikante Prädiktoren für PTBS-Symptomatik am Folgetag darstellten. Darüber hinaus wiesen Alpträume einen prädiktiven Wert für jedes der vier PTBS-Symptomcluster auf. Dieser Zusammenhang war unidirektional Mehrebenenmediationsanalysen legten nahe, dass Alpträume den Zusammenhang zwischen Schlaflosigkeit und PTBS-Symptomen am nächsten Tag mediieren. Diese Ergebnisse stützen dienwachsende Evidenz dafür, dass trauma-assoziierte Schlafstörungen eine wichtige Rolle in der Aufrechterhaltung von PTBS spielen.

Schließlich wurde die in der Literatur belegte reziproke Beziehung zwischen repetitivem negativem Denken (RNT) und negativem Affekt (NA) untersucht (**Studie IV**). Es wurde ein *Statistical Clustering Algorithm* durchgeführt, um diese wechselseitige Beziehung und Dynamik genauer zu explorieren und zu testen, ob Risikogruppen für Psychopathologie über die Assoziation zwischen RNT und NA identifiziert werden können. Aktuelle Studien legen nahe, dass die Stärke der Assoziation zwischen RNT und NA sowohl zwischen Individuen als auch über die Zeit hinweg variieren kann und dass die Ausprägung dieser Assoziation mit späterer Psychopathologie zusammenhängen könnte. Mittels eines *Statistical Clustering Algorithm* wurde untersucht, inwieweit sich die beschriebene Dynamik in

studentischen und allgemeinen Populationen feststellen lässt. Über drei ESM-Datensätze hinweg konnten die Clusteranalysen konsistent zwei Gruppen von Individuen identifizieren, wobei die eine eine Gruppe eine stärkere bidirektionale Beziehung zwischen RNT und NA (und auch eine höhere Trägheit dieser Beziehung über die Zeit) als die andere Gruppe aufwies. Eine längsschnittliche Analyse ergab außerdem, dass Individuen aus der Gruppe mit der stärkeren bidirektionalen Beziehung, die gleichzeitig verstärkt NA erlebten, während der dreimonatigen Follow-Up Periode ein erhöhtes Risiko für die Entwicklung depressiver Symptome hatten. Diese Ergebnisse deuten darauf hin, dass dysfunktionale affektive und kognitive Dynamiken ein vielversprechender Ansatzpunkt für die Prävention psychischer Störungen sein könnten.

In dieser Doktorarbeit wurden mehrere relevante Forschungsfragen beantwortet. Erstens belegt die vorliegende Arbeit, dass der Traumatyp ein wichtiger Moderator ist, den es zu beachten gilt. Die Ergebnisse zeigten, dass die spezifischen Merkmale eines traumatischen Ereignisses Symptomkonstellationen im PTBS-Symptomnetzwerk beeinflussen. Zweitens konnte es Unterschied zwischen *contemporaneous* and *temporal* networks gezeigt werden, was auf die Wichtigkeit verweist, beide Arten von Netzwerken zu untersuchen. Drittens sagte erhöhte Hypervigilanz Veränderungen in den meisten anderen Symptomen im *temporal network* in einer klinischen Stichprobe von PTBS-Patienten vorher, was hinsichtlich Therapieplanung relevant sein könnte. Viertens sagten Schlaflosigkeit und Alpträume PTBS Symptome am nächsten Tag signifikant vorher. Der Effekt von Insomnie auf Symptome scheint dabei über Alpträume vermittelt zu werden. Im Gegensatz dazu gab es keine Veränderungen in Insomnie oder Alpträumen nach Tagen mit erhöhten PTBS Symptomen. Es könnte also sinnvoll sein, in der klinischen Forschung und Praxis Schlaflosigkeit und Alpträume als primäres Behandlungsziel statt als nachrrangige PTBS-Symptome zu sehen.

Schließlich gibt die vorliegende Arbeit Hinweise darauf, wie - basierend auf den festgestellten dynamischen Assoziationen zwischen RNT und NA – in einer jungen Stichprobe Personen mit erhöhtem Risiko für psychische Erkrankungen identiziert werden könnten.

Da sich ESM sowie Netzwerkanalysen im Bereich der Klinischen Psychologie sowie der PTBS-Forschung jedoch noch in der Entwicklungsphase befinden, sollten einige wichtige Einschränkungen und Herausforderungen beachtet werden. Zukünftige Studien sollten darauf vermehrt ihr Augenmerk legen. So sollten zukünftige Studien weiterhin die Bedeutung sowie Nützlichkeit von des ESM-Ansatzes in PTBS-Stichproben untersuchen. Insbesondere sollten Studien dabei prüfen, inwieweit ein ESM-Ansatz gegenüber der retrospektiven Erfassung Vorteile bietet, so wie verstärkt Items spezifisch für den Einsatz mit ESM entwickeln und für Inner-Subjekt-Messungen validieren. Eine kürzlich erschienene Studie von Brose et al (2020) zeigte die Nachteile der bisherigen Vorgehensweise, ursprünglich die für die Messung mit Fragebögen entwickelte Items für ESM-Messungen zu verwenden, deutlich auf, da psychometrische Eigenschaften sich zwischen Inner-Subjekt- und Zwischen-Subjekt-Level unterscheiden.

Weiterhin sollten zukünftige Studien bestimmte statistische Herausforderungen wie Berksons Paradox (ein Typ des Selektionsbias, welcher auftritt, wenn *nodes* im Netzwerk und Einschlusskriterien sehr ähnlich sind; Berkson, 1946) oder Simpsons Paradox (Einfluss einer dritten Variable, welcher auftritt, wenn Rückschlüsse über verschiedene Level hinweg gezogen wegen, z.B. Rückschlüsse von Gesamtpopulationen auf Subgruppen), genau betrachten.

Besonders wichtig scheint zudem, dass *Reduktionismus*, die Erforschung isolierter Phänomene, wenig informativ ist, wenn psychische Erkrankungen als komplexe Systeme betrachtet werden. Neben den psychologischen Variablen (Symptomen) sollten

Netzwerkmodelle daher auch externe Umweltfaktoren, biologische Variablen, sowie deren Zusammenspiel, mitberücksichtigen.

Die vorliegende Thesis birgt ebenso Implikationen für die klinische Praxis. Nach Ehlers & Clark Kognitiven Modell der PTBS (Ehlers & Clark, 2000), ist das sog. Diskriminationstraining eine zentrale Intervention in der PTBS-Therapie. Dabei sollen aktuelle Trigger für Intrusionen gesammelt werden, und Unterschiede zwischen dem traumatischen Event „damals“ vs. der aktuellen Situation „jetzt“ herausgearbeitet werden. Möglicherweise könnte durch die hier verwendete App zur Symptomerfassung bereits eine erste Symptomreduktion erfolgen, wenn Patienten instruiert werden, dieses Diskriminationstraining selbstständig durchzuführen. Da eine große Diskrepanz zwischen der Anzahl von Psychologen pro Einwohner (weniger als 1:100.000; World Health Organization, 2019) sowie dem Smartphone-Besitz (83.96% der Weltbevölkerung; Statista, 2021) besteht, könnten derartige Interventionen eine Alternative für Personen ohne Zugang zu Versorgungsangeboten darstellen.

Zudem besteht weiterhin die Notwendigkeit zu erforschen, ob die Darstellung von Symptomnetzwerken als Ergänzung für Psychoedukation in der Therapie genutzt werden kann, und ob durch das therapeutische Ansetzen an Symptomen mit der höchsten Zentralität mit Netzwerk auch die Intensität anderer Symptome effektiv reduziert werden kann. Um derartige Fragestellungen zu beantworten, müssen experimentelle Studien durchgeführt werden.

Insgesamt zielen die Ergebnisse der vorliegenden Thesis darauf ab, an der allgemeinen Verfeinerung von diagnostischen und therapeutischen Methoden mitzuwirken, insbesondere im Bereich PTBS. Das wichtigste Ziel ist dabei, Personen mit psychischen Belastungen zu helfen.

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