The network approach to psychopathology: From assessment to estimation

Alberto Jover Martínez

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The network approach to psychopathology: From assessment to estimation

Dissertation

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by

Alberto Jover Martínez

Supervisors:

Prof. dr. Anne Roefs

Dr. Lotte Lemmens

Dr. Eiko Fried

Assessment Committee:

Prof. dr. Peter Muris (chair)

Prof. dr. Denny Borsboom, University of Amsterdam

Dr. Omid Ebrahimi, University of Oxford

Prof. dr. Madelon Peters

Prof. dr. Thérèse van Amelsvoort

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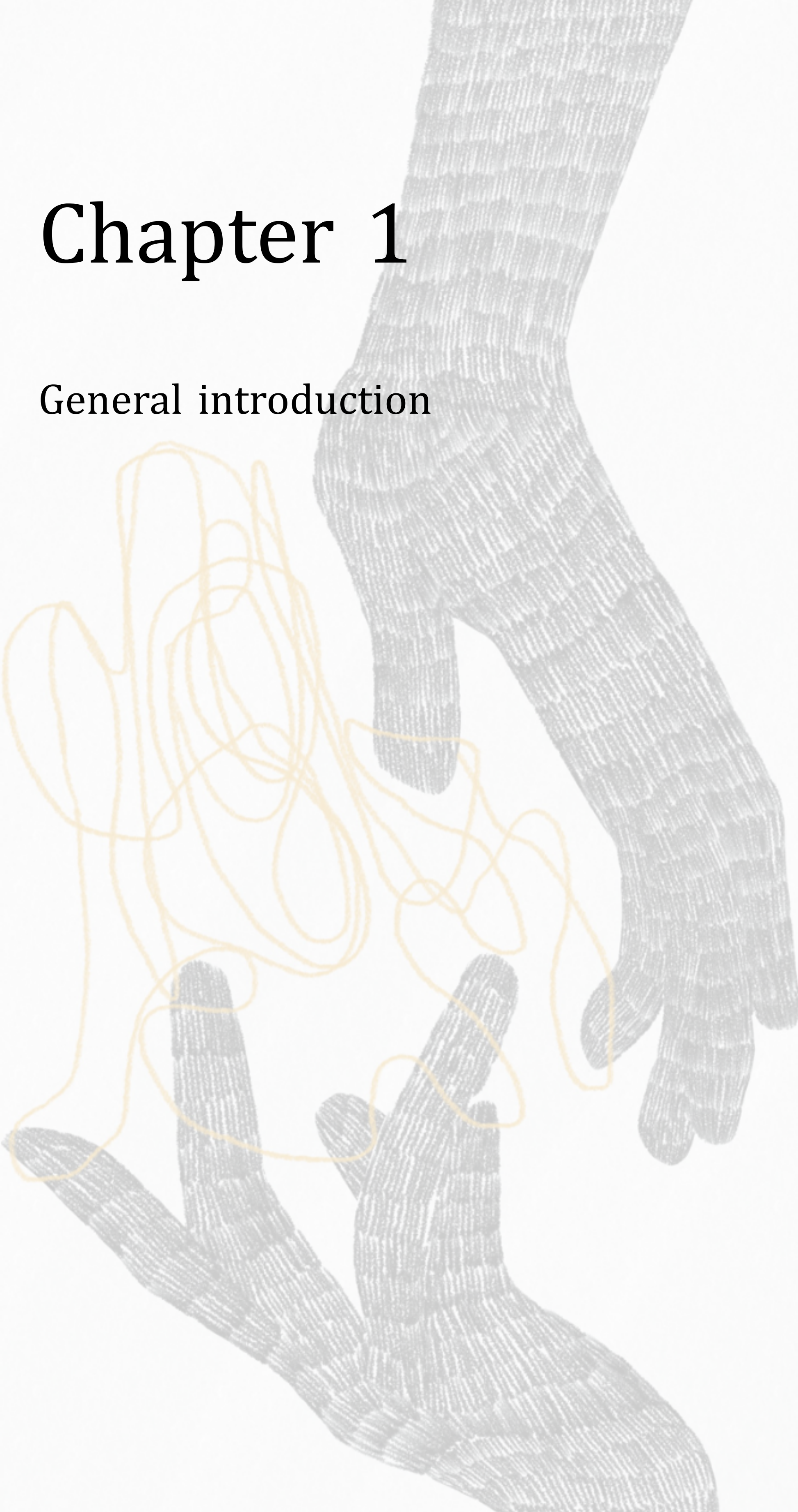
Chapter 1

General introduction



Mental health

The World Health Organization (WHO) defines mental health as "a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well and work well, and contribute to their community" (World Health Organization, 2024). Lack of mental health has become one of the most important public health challenges of our time (Cuijpers, 2019; Lopez & Murray, 1998). Mental health problems are transmitted intergenerationally and affect millions of people worldwide (Beardslee et al., 2011; National Research Council and Institute of Medicine, 2009). Moreover, mental health problems are associated with increased morbidity and mortality (Cuijpers et al., 2014; Liu et al., 2017). All this leads to widespread, large economic costs (Bloom et al., 2012) and suffering of patients and their relatives (Beardslee et al., 2011; National Research Council and Institute of Medicine, 2009)

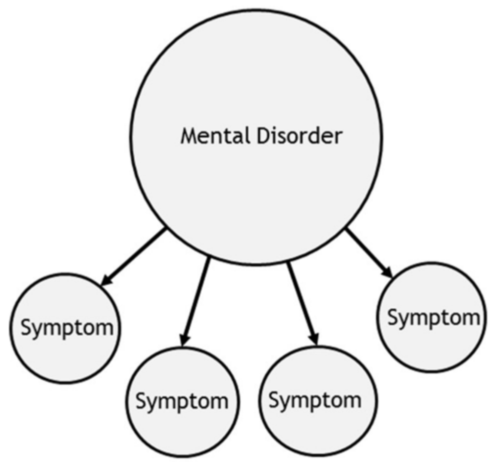
Despite the urgency of improving mental health problems, the treatment efficacy for such problems is modest at best. It is undeniable that treatments for mental health problems are effective across a range of settings (e.g., research-oriented labs or practice-oriented clinics). In general, 79% of clients receiving psychotherapy are better off than people who do not receive treatment (Campbell et al., 2013). However, not only are mental health problems less likely to be treated than physical illness (Clark, 2018; Layard & Clark, 2015), but the outcome of such treatments is poor across the lifespan and different types of psychological problems (Holmes et al., 2018; Reynolds et al., 2012). Moreover, those who benefit from treatment are unlikely to sustain their recovery over time (Clark, 2018; Layard & Clark, 2015). The insufficient success of mental health treatments suggests that such problems are not fully understood (Cuijpers, 2019; Holmes et al., 2014, 2018).

The dominant framework to understand mental health problems is the medical model. This model sees mental health problems as underlying symptoms of mental disorders (Bruce, 2009; Deacon, 2013; Deacon & Lickel, 2009). Classification systems such as the Diagnostic and Statistical Manual of Mental Disorders 5th ed. (DSM-5; American Psychiatric Association, 2013) have been developed based on the medical model (Deacon, 2013). The DSM-5 is widely used in both clinical practice and research (Cuijpers, 2019). Therefore, both the medical model and the DSM-5 have a big impact on the understanding and treatment of mental health problems. However, both the medical model and DSM-5 have received different criticisms in the last decades, casting doubts about their clinical and explanatory potential.

Alternatives to the medical model have been proposed with the aspiration of providing a better understanding of mental health problems. One such alternative is the network approach to mental disorders (Borsboom, 2017). This approach posits that symptoms of mental health problems are not caused by an underlying common cause, but that dynamic interactions between symptoms and other factors constitute the disorder (Borsboom, 2017; Borsboom & Cramer, 2013; Cramer et al., 2010). The overall goal of this thesis is to advance the understanding of the network approach to psychopathology with a focus on measurement development, relationship of baseline psychopathology severity with dynamic network characteristics, network differences between groups with different levels of psychopathology, and inter-individual heterogeneity of these networks. In this chapter, a thorough explanation of the medical model will be provided followed by an introduction of alternative models including the network approach to psychopathology. Afterwards, an in-depth introduction to network methodology, and a description of empirical findings from the network approach is provided. Finally, a description is this thesis' contents is explained per chapter.

Figure 1.

Visual representation of the medical model of mental disorders.



Note. Adapted from "Commentary: A network theory of mental disorders," by P.J. Jones, A. Heeren, and R.J. McNally, 2017, Frontiers in Psychology, 8, p. 2. CC BY-DEED 4.0

Views of mental health problems

The medical model is the most widely used framework to understand diseases, including "mental disorders" (Hyland, 2011). This model posits that symptoms are provoked by an underlying disorder, an underlying common cause (see Figure 1; Deacon & Lickel, 2009; Hyland, 2011) theorized to be located in the brain in the case of mental disorders (Bruce, 2009; Deacon, 2013). For example, this model would say that if a person experiences persistent sadness, excessive sleep, lack of pleasure, low energy, and fatigue, this is caused by an underlying latent factor (e.g., depression), likely located in the brain. This model dominates mental healthcare systems of countries such as the United States of America (Deacon, 2013).

However, this model has also received major criticisms in the last decades, and research has failed to find empirical support for this view on mental disorders (Borsboom & Cramer, 2013). For example, despite decades of research, to this date there is no biological marker of any mental disorder with sufficient predictive power to inform diagnosis of such disorder (Deacon & Lickel, 2009). Moreover, research has not yet identified a supportable biological explanation of any major mental disorder (Kendler, 2005). Research on the genetics of mental disorders has also failed to develop diagnostic tests, identify causes, or develop gene therapies for mental disorders (Deacon & Lickel, 2009). Finally, there is no valid test that identifies abnormal brain circuitry for common mental disorders (Deacon & Lickel, 2009). The nature of mental health problems is complex, but looking beyond the brain for answers can be beneficial (Borsboom et al., 2019; Jefferson, 2022).

Further critiques of the medical model of psychopathology often stem from criticisms of the DSM-5. The DSM-5 is a purely descriptive classification system based on the medical model that is agnostic about the causes of mental disorders. This classification system groups symptoms together in different categories. DSM-5 critiques refer mostly to the lack of validity of the categories proposed by the DSM-5 (Greenberg, 2014; Hyman, 2021). First, comorbidity is the rule rather than the exception (i.e., most patients receive more than one diagnosis), showing that the proposed categories' delineations do not reflect reality (Cramer et al., 2010; Kessler et al., 2005; Kim & Eaton, 2015; Lilienfeld, 2014; Nolen-Hoeksema & Watkins, 2011; Sauer-Zavala et al., 2017). Relatedly, the overlap of symptoms between diagnoses is so substantial that some diagnoses consist entirely of symptoms included in other diagnoses (Forbes et al., 2024). Second, the proposed categories are highly heterogeneous, which means that two people with the same diagnoses often display very different symptom profiles (Fried et al., 2020; Fried & Nesse, 2016). Third, there is evidence suggesting that mental health problems should not be viewed as distinct entities, but as dimensions on which some individuals score higher and others lower (Krueger et al., 2014, 2018; Widiger & Samuel, 2005). Finally, there is evidence showing that different scales aiming at measuring certain DSM-5 categories are very heterogeneous. Specifically, the content overlap of such scales is low although they attempt to measure the same construct (Fried, 2017).

Considering the critiques of the medical model and the resultant DSM-5, it suggests that we do not fully understand mental health. Relatedly, it is unlikely that treatment effectiveness will improve without a better understanding of mental health problems. Therefore, new ways of understanding mental health problems are needed to improve the knowledge on mental health problems and the effectiveness of their treatments.

Alternative frameworks

Transdiagnostic turn

Transdiagnostic models have emerged in response to categorical systems like the DSM-5. These models remove the distinctions between disorders proposed by such classification systems (Dalgleish et al., 2020) and focus on mechanisms, as focusing on diagnoses might overlook fundamental pathological mechanisms (Insel et al., 2010). So, transdiagnostic models focus on underlying pathological mechanisms that are shared across traditional diagnoses. Moreover, these models do not see such mechanisms categorically, but dimensionally. This vision implies that categorising people based on these mechanisms does not make sense because these mechanisms are not simply present or absent, but are present in varying degrees. For example, a person's lack of social support may cause mood problems. However, although this person may be suffering, they may not yet be experiencing a full-blown depressive episode.

One example of a transdiagnostic model is the Research Domain Criteria (RdoC; Insel et al., 2010). The RDoC transdiagnostic mechanisms include negative valence systems (such as fear and avoidance), positive valence systems (such as pleasure and reward seeking), cognitive systems (such as working memory), systems for social processes (such as dominance), and arousal or regulatory systems (such as the sleep-wake cycle). Deficits in these systems are theorized to provoke symptoms across DSM-5 diagnoses. Numerous studies have provided evidence that the RdoC can integrate such systems across levels of explanations (e.g., brain function, environmental, developmental, or behavioral) to better understand certain mental disorders. This has treatment implications as interventions can develop targets at such different levels (Pacheco et al., 2022). Unlike the DSM-5, RdoC tackles comorbidity by studying mechanisms shared across traditional diagnoses, and by taking a dimensional approach.

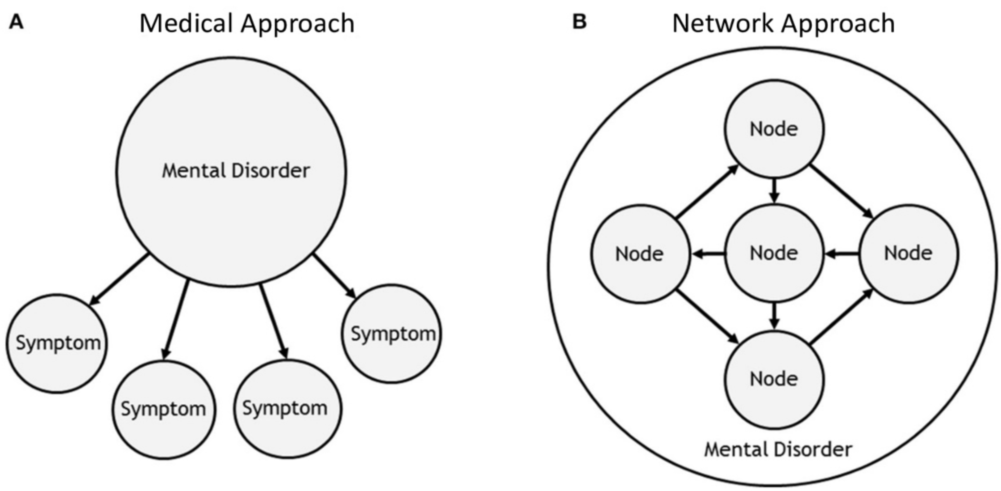
Another example of a transdiagnostic model is the Hierarchical Taxonomy of Psychopathology (HiTOP; Forbes et al., 2024; Kotov et al., 2017). The goal of HiTOP is carrying out empirical research on psychopathology structures, beginning with the most fundamental elements and progressing to the highest level of generality. Specifically, it organizes individual symptoms into components or traits, which are then grouped into empirically-derived syndromes and broader spectra like internalizing and externalizing. There is some evidence supporting HiTOP’s spectra, such as the externalizing spectrum, ranging from impulse control to severe disinhibition (Krueger et al., 2021). Moreover, this spectrum has shown good predictive validity, helping in understanding the progression of some behaviors such as substance abuse (Krueger et al., 2021). HiTOP addresses some limitations of the DSM-5 by reducing within-disorder heterogeneity and tackling comorbidity through the classification of symptom combinations into higher-order components. For example, symptoms like alcohol abuse and aggressiveness can be grouped in the disinhibited externalizing component, although alcohol abuse alone is a lower-level component of harmful substance abuse. Finally, HiTOP tackles the categorization system by taking a dimensional approach.

The network approach to psychopathology

A different approach to mental health problems, and the central focus of this thesis, is the network approach to psychopathology. This approach, like RdoC and HiTOP, is transdiagnostic in nature. However, the network approach differs from RdoC, HiTOP, and the medical model in their explanation of psychopathology. Whereas RdoC and HiTOP do not negate the medical's model view that symptoms are provoked by underlying factors or mechanisms (see figure 2; Jones et al., 2017), the network approach does. Specifically, the network approach posits that dynamic causal interactions between symptoms constitute the disorder itself (Borsboom, 2017). Visual representations of networks represent symptoms as nodes and relations between nodes as edges (see Figure 2).

Figure 2.

Visual representation of a medical vs. network approach to psychopathology.



Note. Panel A represents the medical view of psychopathology where a latent variable (i.e., a mental disorder) provokes the symptoms. Panel B represents the network approach to psychopathology where mental health problems are provoked by the interactions between nodes. In the network approach nodes correspond to symptoms, but in more recent versions nodes can be psychopathology-relevant variables other than symptoms. Adapted from "Commentary: A network theory of mental disorders," by P.J. Jones, A. Heeren, and R.J. McNally, 2017, Frontiers in Psychology, 8, p. 2. CC BY-DEED 4.0

This dynamical view implies a personalized and idiographic approach to mental health problems, i.e., idiographic approaches focus on the study of intraindividual variation

(Molenaar, 2004). In other words, a dynamical idiographic perspective puts the focus on how a person's symptoms unfold over time. That focus on the time dimension allows the study of intra-individual processes (Molenaar, 2004), rendering the network approach a person-focused approach. Advocates of this approach later suggested to include factors other than symptoms in such dynamic processes like behaviors, (social) context, cognitions (Bringmann, 2024; Roefs et al., 2022) or even biological factors such as inflammation levels (Fried et al., 2020). An element external to the network may trigger a symptom which spreads activation to other symptoms. Finally, those symptoms can stay active causing each other even when the external event is absent.

Imagine Pablo, a 30 year old male who, amongst other things, loves climbing. Until a couple of months ago, Pablo was climbing regularly and living his best life. Nothing was really wrong in his life (see first phase of figure 3). However, climbing can be a traumatic and dangerous activity. Between 30% to 50% of climbers experience injuries at some point, with some of the cases resulting in fatality (Kovářová et al., 2024). Imagine Pablo suffers an injury at some point. Thankfully, it is not fatal, but it is bad enough to prevent him from climbing for a while. Not being able to climb would make Pablo feel sad, as it is one of his hobbies. Moreover, as he does not engage in physical activities, he is not as tired at night, which prevents him from sleeping. Finally, he thinks that since he is not exercising much he might gain weight. A thought that makes him anxious, which in turn hampers his sleep even more, and makes him sad as he does not want to gain weight (see second phase of figure 3). This is just the beginning; one month later his lack of sleep is having consequences. Specifically, every time he does not sleep he gets even more anxious about not sleeping, as this lack of sleep brings about problems such as being tired, and irritated. These feelings of irritation makes him more prone to argue with his close ones, which in turn makes him sad (see third phase of figure 3). Nowadays Pablo does not suffer from his injury anymore, but all the previously mentioned psychological and behavioral experiences persist (see last phase of figure 3).

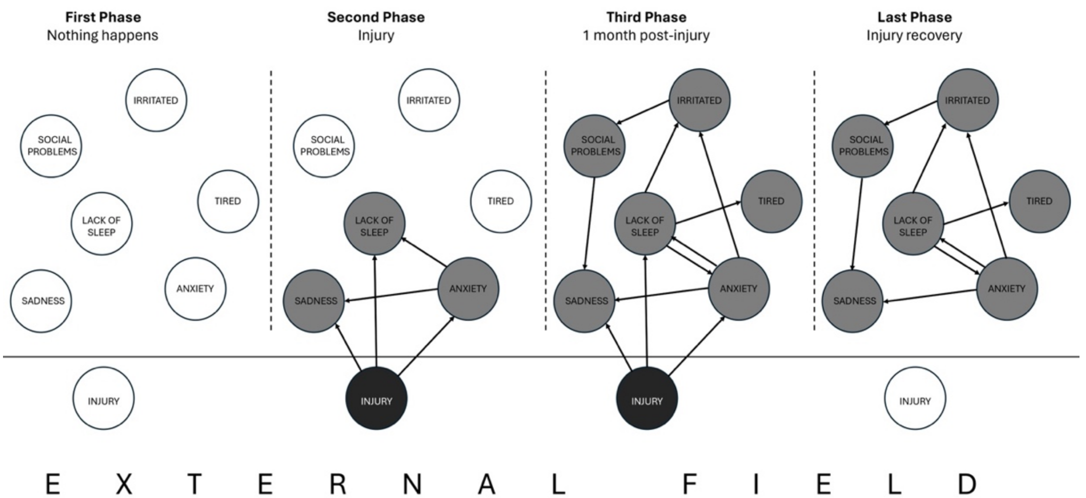
Notice that many of Pablo's described experiences are listed in the DSM-5 list of symptoms of Major Depressive Disorder (MDD). In fact, if symptoms are present long enough, considering that in the end he gained weight, it could be argued that Pablo meets the criteria to be diagnosed with MDD. However, according to the network approach, Pablo does not have MDD, he is experiencing "a problem of living" (Borsboom, 2017, pp. 5) which is reflected in a serie of dynamical and causal interactions between experiences of different nature (e.g., psychological, behavioral, cognitive, social) that are considered symptoms from a medical model perspective.

By getting rid of diagnoses and taking an idiographic focus, the network approach to psychopathology tackles the previously mentioned criticisms of the medical model and the DSM-5. First, the focus on causal dynamics implies a mechanistic focus instead of a descriptive focus. In other words, the focus is not on what symptoms co-occur, but on the processes leading to symptoms. Second, as diagnoses are not necessary to explain psychopathology, their validity is no longer of interest. Said differently, if the idea that an underlying latent factor (i.e., a disease), represented by a diagnosis, is abandoned, studying and improving the diagnosis' validity is not necessary anymore. Consequently, within diagnosis heterogeneity (i.e., how different people's symptom profiles with the same diagnoses can be), and between-diagnoses overlap (i.e., the extent to which different diagnoses include the same symptoms in their criteria) is no long of interest as diagnoses are not the focus anymore. Finally, the idiographic take of the network approach shifts the focus on individuals and acknowledges their heterogeneity.

Additionally, the network approach offers a mechanistic explanation of why individuals may suffer from more than one mental disorder. Instead of explaining comorbidity as a bidirectional relationship between two mental disorders (i.e., both mental

Figure 3.

Visual depiction of Pablo's psychological experiences after suffering a climbing injury. Nodes depict factors relevant for Pablo's experiences.



Note. Arrows depict an effect from a node to another node. Green arrows depict that an increase in the levels of the node of origin leads to an increase in the levels of the ending node. Red arrows depict that an increase in the levels of the node of origin leads to a decrease in the levels of the ending node. The black line surrounding a number of nodes represents the limit of the system known as Pablo. Nodes inside that line are Pablo's internal experiences, and nodes outside that line are experiences outside Pablo.

disorders provoke each other), it states that the onset of symptoms included in the criteria of two disorders spread the activation from one disorder to the other (Cramer et al., 2010). This approach to tackling the critiques on the medical model and the DSM-5 renders the network approach a promising alternative to understanding and treating psychopathology, which goes beyond other alternatives to DSM-V, such as HiTOP and RdoC.

To help understand psychopathology and inform treatments of mental health problems, different features are derived from networks. Such features are divided into global features (i.e., features referring to properties of the network as a whole) and local features (i.e., features referring to properties of specific elements of the network such as nodes, or edges). An example of a global feature is network connectivity, also known as network density. Network connectivity quantifies the overall level of connection of a network. Some authors theorize that networks of people with a higher level of psychopathology (i.e., networks of diagnosed individuals) are more strongly connected as compared to those of healthy individuals (Borsboom, 2017; Wigman et al., 2013, 2015). This is known as the connectivity hypothesis.

Examples of local features are strength, closeness, and betweenness. Strength quantifies how well a node is connected to other nodes (Epskamp, Borsboom, et al., 2018). Closeness quantifies how well a node is indirectly connected to other nodes (Epskamp, Borsboom, et al., 2018). Finally, betweenness quantifies how important a node is in the indirect connection between other nodes (Epskamp, Borsboom, et al., 2018). Some authors theorize that central nodes are more likely to spread activation throughout the network. These nodes are theorized to be important intervention targets, which is called the centrality hypothesis (Cramer et al., 2010). However, local features are controversial as they come from fields different to psychopathology and some authors question their validity (Bringmann et al., 2019).

Network methodology

When the network approach to psychopathology was first proposed, there were no established methods to estimate networks from data (Robinaugh et al., 2020). Since then, a growing body of literature developing methods to study the network approach to psychopathology has emerged. Here, I will describe the most commonly used statistical models, organized according to the type of data these models deal with.

Cross sectional data

Cross-sectional networks. Cross-sectional networks deal with data measured at a single time point in time in all individuals of a group (Borsboom et al., 2021). As variables are measured at a single time point, edges in these networks are non-directional, and reflect cross-sectional relations. One assumption of these models is that data are independent from each other. The resulting models reflect differences between individuals (Borsboom et al., 2021). In other words, the edges can be interpreted as between-individuals partial correlations (Armour et al., 2017). Specifically, positive edges between two nodes represent that individuals with high scores for one node will likely have high scores for the other node too. Conversely, negative edges between two nodes represent that individuals with high scores for one node will likely have low scores for the other node.

The most commonly used model to estimate cross-sectional networks in the field of psychology is the pairwise Markov random fields model (PMRF; Lauritzen, 1996; Murphy, 2013). When data is continuous, the most commonly estimated PMRF is the Gaussian Graphical Model (GGM), also known as partial correlation networks (Epskamp & Fried, 2018). This model assumes data to be multivariate normal (Epskamp & Fried, 2018). This model cannot be used when data is binary. In that case, Ising models are used. An example of binary data of psychopathology could be the presence (encoded as 1) or absence (encoded as 0) of symptoms. In this example, edges between two nodes could be interpreted as the probability of a node being present if the other node is present. In other words, positive edges between two nodes represent that when one node is present it is likely that the other node will be present too, whereas negative edges between two nodes represent that when one node is present, it is likely that the other node will be absent. When the data is composed of both categorical and continuous data Mixed Graphical Models (MGM) are used (Haslbeck & Waldorp, 2015).

Intensive longitudinal data

Temporal networks. Temporal networks deal with variables measured at multiple time points (Borsboom et al., 2021). Unlike cross-sectional networks, temporal networks require temporal data. Specifically, intensive longitudinal data is collected by frequently sampling units that are usually individuals, but can also be dyads or groups (Bolger & Laurenceau, 2013). Therefore, unlike cross-sectional networks, temporal networks require a specific data-collection method to collect intensive longitudinal data called Ecological Momentary Assessment (EMA) studies (Shiffman et al., 2008). EMA studies typically use participants' mobile phones to repeatedly sample behaviors and experiences in real time, and in participants' natural environments. Thus, the possibility of studying individual dynamics is not the only advantage of EMA. EMA reduces recall biases and increases ecological validity as individuals are sampled in real time and in their natural environment.

As the repeated observations are collected from the same individuals, longitudinal models do not assume data to be independent from each other. There are longitudinal models available that deal with the data of a single individual (i.e., idiographic models), but there are other models that deal with data from multiple individuals (i.e., nomothetic models). The most frequently used idiographic model is the Vector Autoreggressive (VAR) model. In this model, each variable at a previous time point is regressed on itself and all other variables in the model at a later time point (Brandt & Williams, 2007). Usually, one time point of difference is used, known as lag-1 models (Blanchard et al., 2022). Therefore, edges are temporal relations, usually between between timepoint t- 1 and timepoint t. Temporal relations imply that the edges have a direction, as we know that the effect goes from timepoint t – 1 to timepoint t. The effect cannot go from timepoint t to timepoint t – 1 as that would imply that an effect goes back in time. Therefore, positive edges indicate that an increase in the level of the node the edge starts from at timepoint t – 1 will lead to an increase in the level of the node the edge goes to at timepoint t. Negative edges indicate that an increase in the level of the node the edge starts from at timepoint t – 1 will lead to a decrease in the level of the node the edge goes to at timepoint t.

The most frequently used nomothetic model is the multi-level extensions of VAR, named multi-level VAR (i.e., mlVAR). This model handles data of more than one individual. The way mlVAR integrates data of multiple individuals is by including a set of fixed effects (i.e., average effects across individuals) and random effects (i.e., individual deviations of such effects). Nevertheless, while this model can inform about the degree of variability between individuals, it is a nomothetic model. Therefore, the edges can be interpreted as an average across participants of the temporal relations between nodes.

Contemporaneous and between-individuals networks. Networks other than temporal can be derived from intensive longitudinal data. However, these networks are not dynamic as they do not deal with temporal relations. Specifically, besides the temporal network, a contemporaneous and a between-individuals network can be derived from mlVAR. The contemporaneous network is estimated after temporal effects are controlled, and its edges represent associations within the same time point. The between-individuals network reflects how the nodes are associated on average across people.

Empirical evidence supporting the network approach to psychopathology

Cross-sectional research

Most research to date taking a network approach to psychopathology has focused on the between-individual level, using cross-sectional data (Wichers et al., 2021). This type of research aims at understanding the structure of networks in disorders such as depressive disorders, anxiety disorders, and Post-Traumatic Stress Disorder (PTSD; Robinaugh et al., 2020). In other words, this research aims at identifying patterns of connections between symptoms across people. Moreover, some studies also aim at testing specific network-driven hypotheses such as the connectivity hypothesis or the centrality hypothesis. Networks of different studies consist of symptoms of the same disorder, different disorders, or symptoms and other relevant factors, such as cognitive functioning or social support (Contreras et al., 2019).

For example, strong associations among avoidance symptoms (McNally et al., 2015; Sullivan et al., 2018) and between hypervigilance and startle responses (Armour et al., 2017; Birkeland et al., 2020; Bryant et al., 2017; McNally et al., 2015; Spiller et al., 2017) have been found in a group of patients with PTSD. In depressive disorder, sadness has been found to be associated with loss of pleasure (Beard et al., 2016; Berlim et al., 2021; Bos et al., 2018). Moreover, symptoms such as concentration problems and feeling sad have been found to be central in networks of depressive disorder (Boschloo et al., 2016; Van Borkulo et al., 2015). Similar research in comorbid conditions and other disorders such as anxiety-related disorders, psychotic-related disorders, personality disorders, and substance abuse disorders has been conducted (Contreras et al., 2019).

Studies testing the connectivity hypothesis have found inconsistent results (Wichers et al., 2021), with only some studies finding support for this hypothesis. Two studies found that the networks of participants with higher depressive symptoms displayed higher connectivity levels (Madhoo & Levine, 2016; Santos et al., 2017). Moreover, a study found that people who suffered from depression for longer had stronger connected networks (Baez & Heller, 2020). Finally, one study found that higher connectivity levels predicted worse depression trajectory (Van Borkulo et al., 2015), but another study failed at replicating these results (Schweren et al., 2018). Moreover, two studies reported an increase of connectivity after antidepressant treatment (Berlim et al., 2021; Bos et al., 2018). Therefore, there is mixed evidence for the connectivity hypothesis.

Importantly, as this type of research is cross-sectional, it does not align well with two relevant points of network theory. First, this research does not consider the dynamic interactions between nodes that are at the heart of the network approach to psychopathology. Moreover, as it is group-based research, it neglects the idiographic stance of the network approach. Therefore, dynamic idiographic research is needed to study the network theory.

Temporal research

Taking a dynamic approach requires temporal data, such as intensive longitudinal data (Bolger & Laurenceau, 2013; Molenaar, 2004). This type of research focuses on temporal associations between different variables. These associations inform about how fluctuations in one variable, compared to an individual's typical level, are followed by fluctuations in other variables for that individual. Such temporal associations are valuable as the temporal ordering of the effects can assist with causal interpretations (Borsboom et al., 2021). Most temporal research focuses on depressive disorders (Wichers et al., 2021), but there are studies focusing on other type of disorders, such as Generalized Anxiety Disorder (Peng et al., 2024), Anorexia Nervosa (Levinson et al., 2020), or Borderline Personality Disorder (Franssens et al., 2024). Dynamic reserach can be nomothetic or idiographic, with most research from the network approach taking the former approach.

Such nomothetic research is mostly multivariate, and studies a combination of slower changing phenomena (e.g., sleep problems, loss of interest, or hopelessness about the future) and faster changing phenomena (e.g., loss of energy, worrying, or mood; Bos et al., 2017; Bringmann et al., 2013, 2015; Groen et al., 2019, 2020; Pe et al., 2015; Savelieva et al., 2021; Snippe et al., 2017; Wigman et al., 2015). This research aims at finding associations between nodes (Bringmann et al., 2013), or network-derived treatment targets (e.g., Bringmann et al., 2015). For example, one study found positive associations among all nodes representing positive mood states (i.e., cheerful, pleasant, and relaxed), positive associations among all nodes representing negative moods (i.e., worry, fearful, and sad), and negative associations between the positive and the negative mood nodes (Bringmann et al., 2013). [make bridge to next paragraph]

Research focusing on the connectivity hypothesis has resulted in inconsistent results (Wichers et al., 2021). Specifically, three studies found that healthy controls display lower network connectivity than depressed patients (De Vos et al., 2017; Pe et al., 2015; Wigman et al., 2015), but one study showed that network connectivity did not change after antidepressant or mindfulness-based treatment, but symptom severity did (Snippe et al., 2017). However, whereas this type of research focuses on the dynamic nature of network theory, it neglects its idiographic nature as it is group-based research

Regarding treatment targets, one study compared the network structure of two groups receiving different treatments (i.e., cognitive therapy, and interpersonal therapy). It was expected that symptom dynamics of participants receiving different treatments would differ as both treatments are supposed to work through different mechanisms. However, the networks of the two groups did not differ significantly (Bringmann et al., 2015). Consequently, the authors conclude that treatment targets might be better identified when focusing on person-specific networks, or centrality indices rather than network structure. However, the network approach is idiographic in nature, and group-based research neglects such nature. Therefore, dynamic idiographic research is also needed to understand the network approach to psychopathology.

Studies taking an idiographic approach have studied single individuals (David et al., 2018; Wichers et al., 2016), multiple individuals separately (Wichers et al., 2020), or a combination of studying the individuals of a sample together and separately (De Vos et al., 2017; Fisher et al., 2017). Most of these studies focused on faster changing phenomena, such as mood (De Vos et al., 2017; Wichers et al., 2016, 2020), with a few of such studies combining slower – such as symptoms- and faster changing phenomena (David et al., 2018; Fisher et al., 2017). This type of research aims at studying inter-individual heterogeneity (De Vos et al., 2017; Fisher et al., 2017) or identifying network-informed early warning signals that indicate a transition to a pathological state (e.g., depression) before such transition happens within an individual (Wichers et al., 2016, 2020).

Regarding inter-individual heterogeneity, different studies use visual inspection to study how different the networks of different individuals are. These studies have observed high heterogeneity indicating that network structure differs greatly between individuals (De Vos et al., 2017) and advocate for idiographic approaches (Fisher et al., 2017). However, some authors argue that part of the heterogeneity that some researchers attribute to inter-individual variation might be due sampling variation or other methodological artifacts instead of inter-individual variation (Hoekstra et al., 2023).

Regarding early warning signals, network informed indicators such as increased autocorrelations or temporal effects between nodes have been investigated. The goal is to identify if such indicators can inform of a transition to a pathological state before such transition occurs. For example, a study followed a patient that decided to stop their antidepressant medication during 239 days. This study found different signals that indicated a transition to depression, such as increased autocorrelation and variances between mood states, or increased temporal relations between such states (Wichers et al., 2016).

Studies examining centrality of nodes have found different momentary states (e.g., relentlessness, sadness; Bos et al., 2017) or symptoms (e.g., suicidality, anhedonia;

Bringmann et al., 2015) as the most central nodes. Interestingly, unlike in group-based research, two studies on single individuals investigating this centrality hypothesis found support for this hypothesis (Wichers et al., 2016, 2020). Specifically, individual networks' connectivity increased along with severity of symptoms. Therefore, methodological choices might be associated to differing results (De Vos et al., 2017).

There are inconsistencies between the presented empirical evidence and the network theory (Borsboom, 2017; Roefs et al., 2022). First, whereas network theory is transdiagnostic in nature, most research is carried out focusing on specific clinical diagnoses derived from the DSM-5. This is especially inconsistent as the network theory states that symptoms are not provoked by disorders, but research from this approach focuses on such disorders. Second, the network theory puts the focus on the individual as it acknowledges the high idiosincrasy of psychopathology, but most research from a network approach is group-based, despite the availability of methodologies to study individuals from a network approach. However, most of the research from the network approach of psychopathology is nomothetic. Nomothetic research only generalizes to all individuals in the group under rarely met conditions, such as homogeneity of such individuals, and stationarity of time series (i.e., ergodicity; Molenaar & Campbell, 2009). Therefore, research on the network theory is very rarely transdiagnostic and is mostly nomothetic.

This thesis

The research presented in this thesis examined the network approach to psychopathology transdiagnostically. The first aim was to develop tools to assess psychopathology from a transdiagnostic perspective in daily life. This involved creating measurement tools and investigating their feasibility for use in EMA studies. The second aim was to study networks of psychopathology from a transdiagnostic perspective. This included examining differences in network structure between groups with varying levels of psychopathology, assessing network robustness, and exploring the generalizability from nomothetic to idiographic models, as well as the heterogeneity of idiographic models.

Aim 1. Developing tools to measure psychopathology from a transdiagnostic perspective in daily life

Chapter 2 describes the development and the actual content of a questionnaire that assesses psychopathology from a transdiagnostic perspective in EMA studies. First, a sample of mental health professionals completed an online questionnaire which asked which items should be included in an EMA study assessing the disorders they were specialized in. Clinicians with different specializations participated in the study. Moreover, the clinicians were asked which items should be included for individuals with any disorder (i.e., transdiagnostic items). After that, focus groups with clinical experts of specific disorders were conducted as complementary information. Finally, three researchers labeled the items, and a final list was derived based on how frequent the items were mentioned. It was also ensured that the final list tapped onto the whole spectrum of psychopathology.

Chapter 3 describes the application of the questionnaire described in Chapter 2 in an EMA protocol. Specifically, a 28 days EMA protocol was completed by 262 participants. The rates of compliance and dropout, and the relations of such rates with certain participant characteristics were studied. Moreover the variability of the items (i.e., within- and between-individuals variability) and the items relation to measures of psychopathology was studied. Finally, the subjective experience of the participants who completed the study was investigated.

Aim 2. Study of networks of transdiagnostic psychopathology.

Chapter 4 compares transdiagnostic networks of students with differing levels of psychopathology. To do that, intensive longitudinal data gathered in the EMA protocol described in chapter 3 was used. The goal of chapter 4 was investigating whether each edge was different between groups. To do that a bootstrapping procedure was carried out. In chapter 5 the same data as in chapter 4 was used to study relevant network properties. First, the robustness of a nomothetic dynamic network model was investigated. Second, how well a nomothetic dynamic network model (i.e., mlVAR) generalizes to the idiographic dynamic network models (i.e., graphicalVAR) of each individual in the sample used to estimate the nomothetic model was investigated. Finally, the heterogeneity of idiographic dynamic network models of transdiagnostic psychopathology was studied. Lastly, chapter 6 dicusses main findings, and provides overall conclusions and recommendation for future research.

Chapter 2

Developing a Transdiagnostic Ecological Momentary Assessment Protocol for Psychopathology.

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Abstract:

Objectives: The network approach to psychopathology posits that mental disorders emerge from dynamic interactions among psychopathology-relevant variables. Ecological Momentary Assessment (EMA) is frequently used to assess these variables in daily life. Considering the transdiagnostic nature of the network approach to psychopathology, this study describes the development of a transdiagnostic EMA protocol for psychopathology.

Methods: First, 96 clinicians completed an online survey, providing three EMA constructs for up to three disorders they specialize in, and three EMA constructs relevant across disorders (transdiagnostic constructs). Second, 12 focus groups were conducted with clinical experts for specific types of diagnoses (e.g., mood disorders, anxiety disorders). Finally, a selection of items is reached by consensus. Two raters independently coded the online survey responses, with an inter-rater agreement of 87.3%.

Results: Jaccard indices showed up to 52.6% overlap in EMA items across types of diagnoses. The most frequently reported transdiagnostic constructs were mood, sleep quality, and stress. A final set of EMA items is created based on items' frequency and informativeness, ensuring completeness across diagnoses and minimizing burden.

Conclusions: The described procedure resulted in a feasible EMA protocol to examine psychopathology transdiagnostically. Feasibility was helped by the overlap in mentioned symptoms across disorders. Such overlap raises questions about the validity of DSM categories.

The medical model has been the basis of research and treatment in clinical psychology and psychiatry for decades (Cooper, 1995). This model states that a mental disorder's symptoms are caused by an underlying common cause, typically of biological origin (e.g., genetics, chemical imbalance in the brain; Deacon, 2013; Scull, 2021). The default for diagnosing mental disorders is a classification provided in the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM5; American Psychiatric Association, 2013), which is based on this medical model and has been criticized for its lack of validity (Borsboom, 2008; Fried, 2017; Fried et al., 2020; Regier et al., 2013; Santor et al., 2006) and clinical utility (Holmes et al., 2018; Layard & Clark, 2015; Ruggero et al., 2019).

The network approach to psychopathology has provided an alternative to the medical model positing that the dynamic interplay of symptoms constitutes mental disorders (Borsboom, 2017). Moreover, the network approach is not limited to symptoms of disorders, but also includes other relevant variables, such as certain cognitions, behaviors, and social circumstances (Roefs et al., 2022). Different methodologies have been developed over the years to test this approach using different types of data (Borsboom et al., 2021). A frequently used method to test the network approach uses cross-sectional data in combination with, for example an Ising model, a Gaussian graphical model, or a mixed graphical model (Borsboom et al., 2021). These analyses result in a 'cross-sectional' network, which usually represents individual differences (Borsboom et al., 2021; for examples see Fried et al., 2018; Hoffart et al., 2021; or Van Borkulo et al., 2015). Cross-sectional networks can be useful as exploratory tools (Von Klipstein et al., 2021). However, due to the lack of temporal data, such networks do not provide information about the dynamic interplay within a person that the network approach proposes as a mechanistic explanation of psychopathology. The goal of this study is to develop a measurement protocol that permits the acquisition of temporal data within individuals with an appropriate time-resolution, to optimally test predictions of the network approach to psychopathology.

To study the dynamic interplay between elements that the network approach proposes, we need to consider how the network elements develop over time within an individual (Molenaar, 2004). That is why studies interested in time dynamics use time series analysis, such as the vector autoregressive (VAR) model (Zivot & Wang, 2006), or one of its extensions such as the multi-level VAR (mlVAR; Bringmann et al., 2013). The VAR model provides information about the relationships of each variable at time point t with itself and all other variables at time point t-1 for each individual. The mlVAR model adds a random effects component that distinguishes between- and within-individuals variance. Such models require intensive longitudinal data, as can be collected with Ecological Momentary Assessment (EMA; Shiffman et al., 2008).

EMA studies consist of repeatedly asking participants in-the-moment questions about phenomena relevant for a study (e.g., behaviors, thoughts, experiences, emotions) during a period of time (Shiffman et al., 2008). EMA has several advantages over laboratory and retrospective survey studies. First, EMA permits the study of time dynamics, which feature centrally in the network approach to psychopathology. Second, EMA decreases the risk of recall bias because the assessments concern in-the-moment experiences. Third, EMA is more ecologically valid because the answers are given within the context of daily life. Therefore, EMA is a valuable addition to the toolkit researchers can use to study psychopathology (Russell & Gajos, 2020; Smyth & Stone, 2003; Wenze & Miller, 2010).

Most EMA studies on the network approach have focused on a single disorder, mostly Major Depressive Disorder (MDD; Wichers et al., 2021). Nevertheless, focusing on just one disorder is likely suboptimal because half of the people with a mental disorder receive two or more diagnoses (Kessler et al., 2005; Kim & Eaton, 2015; Lilienfeld, 2014; Nolen-Hoeksema & Watkins, 2011; Sauer-Zavala et al., 2017). According to the network approach, comorbidity occurs because similar symptoms can occur in multiple disorders. The onset of such symptoms increases the likelihood of activating other symptoms, belonging to different disorders as well (comorbidity hypothesis; Cramer et al., 2010). Therefore, it is important to investigate the network approach to psychopathology transdiagnostically, instead of only focusing on single disorders. The current study entails the development of such a transdiagnostic EMA measurement protocol of psychopathology.

To be optimally valuable, an EMA measurement protocol needs to be carefully designed (e.g., number of surveys per day, number of items per survey, schedules of the surveys, randomization of surveys, length of study, etc. need to be considered; Wright & Zimmermann, 2019). In many studies, EMA protocols use items from questionnaires and surveys that are developed for laboratory or retrospective survey studies (Schreuder et al., 2020). Many of those questionnaires are designed to capture either a certain diagnostic category (e.g., anxiety disorders) or a certain transdiagnostic construct (e.g., insomnia). These types of questionnaires do not align well with the network approach, because (1) the focus is often on one diagnostic category or one transdiagnostic construct, (2) questionnaires are often long, and (3) the questions are often framed retrospectively, ask participants to consider a certain past period. Therefore, an EMA measurement protocol for transdiagnostic assessment in daily life and for network modelling purposes is needed (Wichers et al., 2021).

In the current study, we aim to develop a dedicated transdiagnostic EMA protocol for psychopathology. This protocol includes symptoms of mental disorders as well as other psychopathology-relevant variables, such as social context. The comprehensive EMA protocol includes variables that are disorder specific as well as variables that are relevant for multiple disorders. In addition to such transdiagnostic variables, we also aim to incorporate disorder-specific variables that are crucial for specific disorders to ensure the comprehesiveness of the protocol. Developing a measurement protocol encompassing such a large range of variables faces a number of challenges. First, the tradeoff between information gain for researchers and burden for participants. On the one hand, the number of items per measurement moment needs to be limited to mitigate participant burden and promote compliance and careful answering of questions (Eisele et al., 2022). On the other hand, transdiagnostic measurement calls for a broad range of constructs (Eisele et al., 2022). Therefore, it is crucial to carefully select a limited set of items that accurately and optimally capture the phenomena of interest. Second, in EMA studies one needs to consider how dynamic the variables of interest are, that is, the expected fluctuation throughout the day (e.g., it makes little sense to query about sleep quality more than once per day).

These challenges are tackled by leveraging two sources of information. First, an online survey of clinicians is deployed to determine the most informative variables for every disorder. Second, we conduct focus groups with clinical experts of specific disorders. Focus groups are chosen as a complementary, high quality and reliable sources of information to the survey of clinicians. Clinical experts' level of experience over the years renders them a reliable and effective source of information (Rauf et al., 2014; Willis et al., 2009). The EMA protocol is developed following three steps: (1) determining the most relevant items in the online survey, (2) complementing the information from the survey with the information from the focus groups, and (3) coding all information, computing interrater reliability, and carefully selecting a final list of items. The whole process is thoroughly described in the present paper, and the resulting EMA measurement protocol is presented.

Method

Overview

The current study consisted of three steps: (1) an online survey administered to clinicians, (2) focus groups with clinicians of 12 categories of mental disorders, and (3) combining the information gathered from those two sources.

Participants

Survey of clinicians. Our international recruitment targeted officially licensed mental health clinicians (according to own country guidelines), holding at least a master's degree in clinical psychology, psychiatry, or a similar mental health care specialization. Participants were recruited via advertisements distributed among various psychotherapy associations from the Netherlands, the USA, and Europe, and via social media and networks of members of our research team. The survey was approved by the ethical committee of the Faculty of Psychology and Neuroscience of Maastricht University, and was pre-registered on AsPredicted (#62825; https://aspredicted.org/79X_XY5). Of 241 potential participants who clicked on the survey's link, 96 (39.83%) completed it. Participants characteristics can be found in Table 1.

Table 1.

Work-related demographic characteristics of clinicians participating in the survey study (n = 95).

Characteristic	n	%
Position		
Behavioral Scientist	2	2.1
Licensed health psychologist	32	33.7
Licensed child- and youth psychologist	5	5.3
Licensed psychotherapist	15	15.8

Licensed clinical (neuro)psychologist	23	24.2
Psychiatrist	5	5.3
Other	13	13.7
Recruitment source		
A psychotherapy association	57	60.0
LinkedIn	33	34.7
Social media	5	5.3
Country		
Belgium	9	9.5
Germany	4	4.2
Greece	1	1.1
Iceland	1	1.1
Netherlands	77	81.1
New Zealand	1	1.1
Peru	1	1.1

United States of America	1	1.1
Work setting[a]		
General hospital	8	8.4
Mental health care center	64	67.4
Private practice	24	25.3
Other	8	8.4
Type of care[a]		
Inpatient	22	23.2
Outpatient	86	90.5
PhD		
Yes	32	33.7
No	63	66.3
Stream of thought[a]		
Cognitive Behavioral Therapy	70	73.7
Psychoanalytic and/or psychodynamic	16	16.8

EMDR	37	38.9
Family systems	13	13.7
Humanistic	9	9.5
Dialectical behavioral	7	7.4
Interpersonal	15	15.8
Integrative	16	16.8
Emotion focused	15	15.8
Narrative	4	4.2
Motivational interviewing	10	10.2
Other	12	12.6
Main type of patient		
Children and/or adolescents	6	6.3
Adults	82	86.3
Elderly	6	6.3
Families	1	1.1

Work experience		
1-5 years	11	11.6
6-10 years	18	18.9
11-15 years	20	21.1
16-20 years	15	15.8
21-25 years	14	14.7
26-30 years	4	4.2
More than 30 years	13	13.7
Working hours		
1 day or less per week	4	4.2
Between 2 and 4 days per week	60	63.2
Full time (5 days per week)	31	32.6

Note. n = 95 for demographic information, because one participant did not answer the demographic questions. [a]Multiple answers possible.

Focus groups with clinical experts. Experts were selected through purposive sampling, as is often done in focus group research , based on their contribution to their respective clinical and research fields, and were recruited via e-mail. In total, 12 focus groups were carried out, one per disorder group. Most focus groups consisted of 3 experts: mood disorders, anxiety disorders, substance use disorders, eating disorders, somatoform disorders, psychotic disorders, neurodevelopmental disorders, and sexual disorders. The trauma and stressor related disorders, personality disorders, sleep disorders, and conduct disorders focus groups consisted of 2 experts. The focus groups were pre-registered and approved by the faculty's ethical committee (AsPredicted #62825; https://aspredicted.org/79X_XY5).

Design

Online survey of clinicians.

Contents of survey. The survey was administered via the online platform Qualtrics (https://www.qualtrics.com) and inquired about the types of items that clinicians would include for an EMA study investigating the entire range of psychopathology (Roefs et al., 2022). Participants named the three EMA items they considered most relevant for the (up to three) disorders they specialize in. Afterwards, they named 3 EMA items that they would ask people with any disorder (i.e., transdiagnostic items).

Analyses questionnaire. All provided answers (k = 1004) were coded by two independent raters (R1 and R2) and coded to denote the construct the item taps into. For example, both items "Do you feel an urge or a craving to consume drugs right now?" and "Do you have a huge desire to take drugs?" were coded to reflect the same construct "craving". We calculated inter-rater reliability, and afterwards, any disagreements were resolved together with a third rater (R3). Finally, the frequencies of the constructs were explored to determine the more popular ones. The amount of overlap between the different mental disorders' constructs was calculated by means of Jaccard similarity indices. This index ranges between 0 and 1, with higher values indicating more similarity. It is operationalized as the length of the union divided by the size of the intersection between the sets: Jaccard Similarity = (number of observations in both sets) / (number in either set). This operationalization is written in notation form as $J(A, B) = |A \cap B| / |A \cup B|$.

Focus groups.

To ensure that no relevant items were overlooked, we utilized focus groups with clinical experts to gather richer information about relevant items in psychopathology EMA studies. Each focus group consisted of a 90-minutes semi-structured interview and was carried out and recorded via zoom (https://zoom.us). The experts were rewarded with a 15 euros voucher.

Semi-structured interview protocol. Each of focus groups concerned a specific type of mental disorder, making sure that the entire range of psychopathology was covered. There were two parts in each focus group: The first part was concerned with etiology, clinically relevant factors, and theory, and the second part was about the items they would include in the EMA protocol. Experts were also encouraged to think thoroughly if the items should be asked momentarily (i.e., several times per day), daily, or weekly, to ensure that items can be phrased in accordance how they are thought to fluctuate over time.

Putting it all together

The information obtained from the online survey was integrated with the information obtained in the focus groups. First, the most frequently mentioned constructs in the online survey per disorder were selected if such constructs were suitable and informative for a transdiagnostic EMA study. Selection was based on two criteria: (1) sufficient within-person variance was to be expected. For example, an individual's attachment style does not vary frequently enough to warrant multiple assessments during the day. (2) The questions needed to be about concepts that are understood easily by participants. We excluded too complex or abstract concepts, such as the adequacy of an emotional response given a certain situation, and how spiritually fulfilling an activity feels.

Second, the list of constructs obtained from the online survey was complemented with constructs from the focus groups we deemed important from a content perspective while still considering the criteria mentioned above. Third, the number of constructs was reduced to limit participant burden. To do so, R3 and R1 each made a selection of constructs based on two criteria: (1) constructs that were more transdiagnostic (i.e., that were mentioned for more disorders) were favored, (2) constructs that were central for specific disorders were favored (e.g., compulsions may only be relevant for Obsessive Compulsive Disorder rather than the entire group of anxiety disorders, but it is extremely central for this disorder). After the selections were made, there was a discussion to solve the disagreements on the selections. Finally, the list was reduced based on the overall relevance of the constructs to keep the list as short as possible. For each selected construct, an adequately phrased item was formulated, if possible, based on the ESM repository (Van Heck et al., 2018).

Results

Step 1: Online Survey of Clinicians

Table 2 shows a summary of which disorders were most frequently treated by the participating clinicians. Participating clinicians could choose up to three disorders, and they were asked to mention the disorders they treat in treatment-frequency order (i.e., 1st selected disorder is most frequently treated). For determining the underlying constructs (e.g., craving alcohol) that items (e.g., “intense desire to consume alcohol”) listed by clinicians tapped into, the inter-rater agreement was 87.3%. Disagreements between R1 and R2 were resolved by R3. The 5 most frequently mentioned constructs per type of disorder, and the transdiagnostic constructs are summarized in Table 3.

Table 2.

Information on the mental disorders participating clinicians treated.

Category of disorder	1st disorder		2nd disorder		3rd disorder		In total	
	n	%	n	%	n	%	n	%
Anxiety disorders and OCD	13	13.5	7	8.8	16	24.2	36	14.9
Disruptive, impulse-control, and conduct disorders	1	1.0	2	2.5	1	1.5	4	1.7
Eating disorder	2	2.1	1	1.3	1	1.5	4	1.7
Mood disorders	24	25.0	19	23.8	14	21.2	57	23.6
Neurodevelopmental disorders	4	4.2	4	5.0	1	1.5	9	3.7

Personality disorders	24	25.0	14	17.5	8	12.1	46	19.0
Psychotic disorders	6	6.3	4	5.0	5	7.6	15	6.2
Sexual disorders	0	0.0	1	1.3	0	0.0	1	0.4
Somatoform disorders	1	1.0	1	1.3	2	3.0	4	1.7
Sleep disorders	1	1.0	3	3.8	2	3.0	11	4.5
Substance use / addiction disorders	6	6.3	3	3.8	2	3.0	11	4.5
Trauma and stressor disorders	14	14.6	21	26.3	15	22.7	50	20.7
Number of responses	96	100	80	100	66	100	24 2	100

Note. n = 96. Participants could mention up to three main categories of disorders they mostly work with. This table displays the percentage of participants that choose each disorder in each position.

Table 3.

Rank order of the most commonly mentioned constructs for the disorder-specific categories.

Category	1st construct	2nd construct	3rd construct	4th construct	5th construct
Mood disorders	Mood	Energy	Enjoyment	Activity	Suicidal ideation
Anxiety disorders (and OCD)	Anxiety	Avoidance	Coping	Tension	Activity, etc*
Trauma and stress related disorders	Avoidance	Feeling Safe	Flashbacks*	Stress*	Coping
Substance abuse disorders	Urge/Craving	Substance use	Happiness*	Interpersonal Support*	Used amount*
Somatoform disorders	Ability to move	Ability to relax*	Context*	Functioning*	Mood, etc.*
Eating disorders	Body-image*	Compensatory behaviors*	Eating mood*	Self-control*	Self-esteem, etc.*

Psychotic disorders	Anxiety	Paranoid	Auditive hallucinations	Mood	Burden, etc.*
Neurodevelopmental disorders	Concentration*	Mood*	Overstimulation*	Sleep quality*	Alertness, etc. **
Personality disorders	Interpersonal problems*	Interpersonal satisfaction*	Emotion regulation**	Stress**	Interpersonal connectedness, etc. (Mood)***
Sleep disorders	Sleep quality	Feeling rested	Tension*	Energy*	Falling asleep, etc. **
Sexual disorders	Interpersonal sexual	Masturbation	Sexual pain	-	-
Disruptive, impulse-control, and conduct disorders	Anger	Anger management*	Coping strategy*	Fights*	Frustration tolerance, etc. *
All disorders	Mood	Anxiety	Sleep quality	Avoidance	Coping
Transdiagnostic constructs	Mood	Sleep quality	Stress	Anxiety*	Coping*

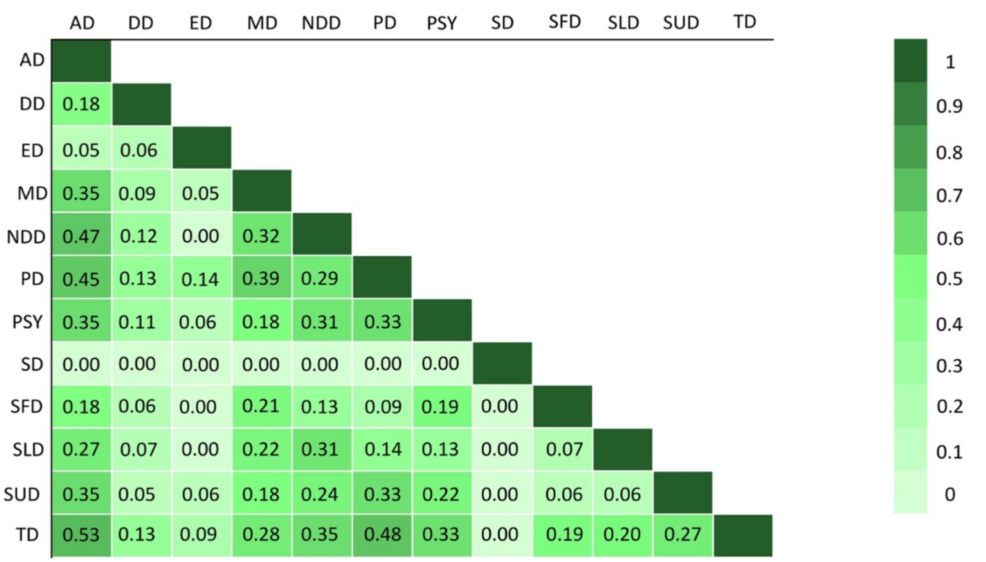
Note. Frequencies were collapsed across disorders, and in the last row across transdiagnostic constructs. The asterisks in this table represent ties. For example, if several constructs are followed by an asterisk "*" those constructs were mentioned the same number of times. Only constructs with the same number of asterisks are tied together.

The largest Jaccard similarity index was observed between the items mentioned for anxiety disorders and trauma and stress related disorders (0.53), followed by personality disorders and trauma and stress related disorders (0.48), and anxiety disorders and neurodevelopmental disorders (0.47). The heatmap in Figure 1 shows the overlap across all disorders.

The degree of overlap between the disorder-specific constructs and the transdiagnostic constructs was investigated by means of Jaccard similarity indices as well. The top 3 most mentioned transdiagnostic constructs were mood, sleep quality, and stress. As Figure 2 displays, at least one transdiagnostic construct was also mentioned as a disorder-specific constructs for all disorders, except for sexual disorders. All three transdiagnostic constructs were mentioned for anxiety disorders, and trauma and stressor-related disorders.

Figure 1.

Heatmap Jaccard Similarity Indices for all Categories of Disorders.



Note. Note. AD = anxiety disorders. DD = disruptive, impulse-control, and conduct disorders. ED = eating disorders. MD = mood disorders. NDD = neurodevelopmental disorders. PD = personality disorders. PSY = psychotic disorders. SD = sexual disorders. SFD = somatoform disorders. SLD = sleep disorders. SUD = substance use/ addiction disorders. TD = trauma and stress related disorders. This heatmap shows the amount of overlap between disorders. An index of 1 means total overlap,

Figure 2.

Overlap between transdiagnostic constructs mentioned and disorder-specific constructs.

Construct	AD	DD	ED	MD	NDD	PD	PSY	SD	SFD	SLD	SUD	TD
Mood	x			x	x	x	x		x		x	x
Sleep quality	x			x	x					x		x
Stress	x	x	x			x						x
Jaccard similarity index	1.0	0.33	0.33	0.67	0.67	0.67	0.33	0	0.33	0.33	0.33	1.0

Note. AD = anxiety disorders. DD = disruptive, impulse-control, and conduct disorders. ED = eating disorders. MD = mood disorders. NDD = neurodevelopmental disorders. PD = personality disorders. PSY = psychotic disorders. SD = sexual disorders. SFD = somatoform disorders. SLD = sleep disorders. SUD = substance use/ addiction disorders. TD = trauma and stressor related disorders.

Step 2: Focus groups

Supplementary table A shows an overview of the constructs proposed by the focus groups divided in the momentary questions, daily questions, and weekly constructs. Most suggested constructs varied throughout the day, and overlapped considerably across focus groups. For example, mood was mentioned in six focus groups, and stress as well as avoidance in four. These constructs, as well as other constructs that varied throughout the day, were included in the final questionnaire. Some focus groups, such as the focus groups for sleep disorders and personality disorders, did not mention many constructs that varied throughout the day. In these focus groups, it was considered that constructs that varied more slowly (e.g., that varied from day to day, or from week to week) were more relevant for that type of psychopathology. Of these daily and weekly constructs, there was some overlap across focus groups. For example, sleep was mentioned in eight focus groups, substance use in three, and medication in two. These constructs were included as daily constructs in the final questionnaire. The fewest constructs were gathered for the weekly constructs, for which only suicidality was mentioned sufficiently commonly to warrant inclusion.

Step 3: Putting it All Together

There was considerable overlap between the online survey and the focus groups. However, some constructs were only mentioned in the focus groups. Some of these constructs were included in the EMA protocol due to their relevance. For example, feeling lonely, loss of control, and life meaning were constructs that were only mentioned in the focus groups, and were included in the EMA protocol.

The resulting EMA questionnaire includes a maximum of 35 momentary items, 26 daily items, and 4 weekly items, which can be found in Supplement B. Some surveys may include fewer items due to conditional branching (e.g., if participants state that they are alone, they will not be asked who they are with).

All included questions were phrased on 7-point Likert scales. A 7-point Likert scale is used because it is within the optimal range of options (Simms et al., 2019), to permit participants to select a middle point (i.e., answering option 4 on the 7-point scale), and to enable sufficiently fine-grained answering. Likert scales were used rather than Visual Analogues Scales (VAS) because they are faster to answer, and easier to use for younger and older people, and populations with a lower education level (Fryer & Nakao, 2020). Moreover, quantification of answers is easier for Likert scales (Trimmel & Trimmel, 2017), and psychometric properties are comparable to VAS (Simms et al., 2019).

Discussion

In the present study, a comprehensive transdiagnostic EMA protocol for psychopathology was developed based on an online survey completed by clinicians and focus groups with clinicians. The degree of overlap across disorders, as well as between disorder-specific and transdiagnostic constructs was explored. The degree of overlap was substantial between disorders, including the transdiagnostic constructs. This overlap helped in keeping the final set of EMA items within acceptable limits for participants and underlines the rationale for studying psychopathology transdiagnostically. The study resulted in an EMA measurement protocol consisting of up to 35 momentary items, up to 26 daily items, and 4 weekly items (some items may not be answered due to conditional branching).

As expected from a transdiagnostic approach, the degree of overlap across the different mental disorders was substantial. In some cases, almost half of the disorder-specific answers overlapped between two disorders, and in one case – between anxiety disorders and trauma and stress related disorders – the overlap was above 50%. Similarly, the transdiagnostic constructs overlapped considerably with the disorder-specific constructs. Only for sexual disorders, no overlap was found with the top-3 transdiagnostic constructs. Note that a limitation of the present study is that for some disorders only few responses (i.e., fewer than 10) were obtained in the online survey, because we assesed a limited number of clinicians treating such disorders. However, this lack of responses was compensated by the information obtained in the focus groups. Other limitations of the online survey are the overrepresentation of some nationalities (i.e., Dutch clinicians) and that the patients' perspective was not considered. Future research should address these limitations.

The large overlap across disorders makes sense considering the overlap of criteria between DSM categories (Forbes et al., 2024). Such overlap between diagnoses casts doubts on the validity of the DSM categories because they do not seem to be well delineated. Promising alternative classifications of psychopathology, such as the Hierarchical Taxonomy of Psychopathology (HiTOP; Ruggero et al., 2019), and the Research Domain Criteria (RDoC; Insel et al., 2010) project also attempt to circumvent these problems of the DSM classification. The network approach goes one step further, as it takes an idiographic perspective to psychopathology. Moreover, the network approach shares a vision on comorbidity with Hi-TOP and RDoC that aligns with the present results: "There are also symptoms that do not clearly belong to one or the other disorder, because they receive and send out effects to the symptoms in both of the disorders (i.e., overlapping symptoms) [...] which we propose to call a bridge symptom. We hypothesize that in clinical practice, such bridge symptoms turn up as symptoms that are used in diagnostic schemes, such as the DSM-IV, for multiple disorders." (Cramer et al., 2010, p.140). Therefore, comorbidity is not due to a (bi)directional relationship between two latent factors (i.e., disorders). Instead, it is due to the effects that spread out from bridge symptoms. The observed overlap of constructs between disorders suggests that there could be plenty of such bridge symptoms.

A number of studies have investigated comorbidity from a network approach. Most of these studies were cross-sectional and focused on comorbidity between MDD and symptoms of other disorders, such as generalized anxiety disorder, post-traumatic stress disorder, bulimia nervosa, substance use disorder, or bipolar disorder. Some studies observed that symptoms of those disorders often co-occur , whereas others do not (De Haan et al., 2020; Rogers et al., 2019). The studies suggest some methodological explanations about why not bridge symptoms were found, like large number of nodes in the network model, considerable quantity of missing data for many items, and the methodological challenges associated with imputing missing values in network analyses.

However, another possibility suggested is that bridge symptoms do not have time to manifest in fast episodes of a disorder. Instead, they may manifest during more chronic episodes when there is time for such symptoms to unfold.

A recent review of network studies only found two studies who use temporal data to study comorbidity (Wichers et al., 2021). For these studies, the results are also mixed: one study found large individual differences in bridge symptoms (Kaiser & Laireiter, 2018), whereas the other did not find any evidence thereof (Groen et al., 2020). The authors mention that their study design did not allow for the investigation of bridge symptoms during all phases of psychopathology development. They suggest that bridge mental states may be more relevant during the period when comorbidity first develops or re-develops. For this reason, it is crucial to develop ways to determine when is the best moment to assess variables. Future research should explore whether triggers based on passive data or warning signals (e.g., a threshold score) can be used to signal when a variable can best be assessed.

The EMA protocol resulting from this study opens the possibility to study psychopathology from a transdiagnostic approach in daily life. Developing a measurement protocol like this is necessarily partly a subjective process. This study attempted to reduce the degree of subjectivity as much as possible and to include the most clinically relevant items. Several design strengths contributed to these goals. First, expert clinicians were asked for input, guaranteeing a close link with clinical practice. Second, participants and experts were explicitly asked to mention variables that were expected to fluctuate throughout the day, making them suitable for inclusion in an EMA protocol. Third, all ratings were conducted independently by at least two researchers, and any disagreements were settled in consultation with a third researcher, reducing subjectivity.

Notable as well is that the time scale was adapted to the type of variable that was assessed: momentary items (8 times per day), morning items, evening items, and weekly items, based on the expected degree of fluctuation. For example, it makes sense to ask about mood several times a day, whereas it suffices to assess sleep quality only in the morning. Therefore, psychological phenomena must be asked at the proper time scale to properly capture fluctuations and to reduce participant burden. Some researchers have already highlighted the relevance of distinguishing the time scales of different psychological phenomena (Wichers et al., 2021). Specifically, research suggests that different psychological phenomena exert their influence at a different level (Wichers et al., 2021). Specifically, the dynamics between micro-level momentary affective states are actually the building blocks for the development or maintenance macro-level symptoms.

This difference requires different methodological considerations such as a different measurement frequency.

Unfortunately, network estimation methods are not able to deal with variables measured at a different time scales yet, despite how central that is for the network approach to psychopathology. Therefore, it is crucial to develop methods to determine variables' optimal time scale, and methods to combine variables measured at different time scales. A possible way to determine a variable's optimal time scale might be fitting autoreggressive models with longer lags to see which lag is more predictive. Variables which variance is better accounted for with longer lags might be better captured with longer time scales. Regarding possible ways of modelling variables measured at different frequencies,multi-layered networks might be a possibility. With this approach, variables measured at the same frequency could be used to build a network, which would lead to a network per used assessment frequency. Next, the the networks for each assessment frequency can be integrated in a multi-layer network (Blanken et al., 2021).

Taken together, the results of this study suggest that a transdiagnostic approach to psychopathology, and its study in daily life within individuals, is a promising direction of research, which can now be explored in EMA studies. Moreover, this approach fits well with the network approach to psychopathology. The usefulness of this questionnaire extends beyond the study of the network approach to psychopathology in daily life. The time-series data that can be obtained with this protocol can be analyzed in different ways from different perspectives. Data will need to be collected to test if there is enough within-subjects variance for each item, if the present questionnaire is related to standardized measures of psychopathology, and to determine if any changes regarding the measurement frequency are needed (Schreuder et al., 2020). If items are asked at a time scale that is not frequent enough, the variations will not be captured, and if they are asked too frequently, the participant burden is unnecessarily high. Moreover, the validity and reliability of the EMA protocol needs to be studied as well. The EMA protocol can then be further refined for future studies.

Supplementary materials

Supplementary table A1.

Proposed momentary constructs by the focus groups.

MD	AD	ED	TD	SUB	SFD	PSY	SD	SLD	PD	DD	NDD
Other Activity	Tension	Feelings of control	Intrusions	Substance: type, amount, frequency	Somatic symptoms	Hallucinations	Sexual desire	Sleepiness	Coping styles	Anger/Annoyed/ irritated/frustrated	Restlessness
Mood	Other Activity	Concerns	Avoidance	Craving	Worry about symptoms	Suspiciousness	Sexual arousal	Alertness	How are you doing?	Revenge-plotting	What are you doing wrong?
Positive Affect	Avoidance	Negative feelings about body	Hyperarousal/startle response	Anxiety	Stress	Delusions	Object of arousal	Mood	Levels of personality scale	Thinking of bad things to do	Forgetfulness

Anhedonia	Mood	Preoccupation about food and eating	Detachment	Mood	Avoidance/ coping	Hyperarousal	Fantasizing			Guilt	Distractibility
Motivation	Sadness	Compensatory behaviours	Concentration	Daily activities	What do you think that causes your complaints	Loss of control	Sexual activity			Do you want to annoy people?	Social interaction
Restlessness	Happiness	Avoidance of seeing the body	Coping style	Do people around you use	Preoccupation (body check, thinking about complaints)	Preoccupation	Feelings about sexual activity			Verbal/physical aggression	Mood/mood swings
Tension	Energetic	Body checking		Are you intoxicated	Overload	Social experiences	Level of stress			Did you do something bad without thinking	Menstruation cycle
Anxiety	Tiredness	Self-criticism		Context	Pain coping behaviours	People around	Relationship satisfaction			Self-control	Hormonal contraception

Nervousness	Bodily symptoms	Eating pattern		Stress	Limitations in functioning as a consequence of symptoms	anhedonia	Perceived partner responsiveness			Resentment, mistrust, cynicism	Social support
Rumination	Context	Interpersonal relations		Boredom		Reliving experiences	Time spent with partner			Perceived wrongdoing	Task-focus
Activity	Mulling	Behaviour in life				Mood	Level of interaction			Guiltiness	Irritability
											Focus/concentration
											Fatigue

Supplementary table A2.

Proposed daily items by the focus groups.

MD	AD	ED	TD	SUB	SFD	PSY	SD	SLD	PD	DD	NDD
Sleep	Panic attack	Sleep	Intrusions	Sleep quality	Sleep	Sleep	Sexual problems	How did you sleep?	Daily quality of life	Too angry /easily annoyed	Sleep
Substance use	avoidance	How was your day	Detachment	Amount of drinks	Resting	Emotion regulation	Catastrophizi ng	How much did you sleep?	Interpersonal tension	Substance use	

Perspective/ hope	Time spent in compulsions	Binges		Were you intoxicated when filling out the surveys?	Physical/ mental/ social limitations		Relationship conflicts	Physically tense	Interpersonal stressful events		Medication
Self-esteem	Time spent worrying	Restrain		Drug usage	Activity levels		Coping with relationship conflict	Mentally alert	Demoralisati on		Compliance to medication
Self-confidence	Sleep	Self-harm		Meaningful activity	Medication use		Initiative to have sex	Daily functioning			Eating pattern
Enjoyment (food)	Suicidal ideation	(bad) memories		Physical wellbeing	Acceptance						Functioning

coping	Compensation behaviors	Information seeking on internet	How ordered is your house today?
Is there someone I can talk to?	Body checking behaviors		Social interactions
Meaning in life	Avoidance		Social media
Satisfaction in life			How was your day?

Purpose in life

How was your day

Supplementary table A3.

Proposed weekly constructs by the focus groups.

MD	AD	ED	TD	SUB	SFD	PSY	SD	SLD	PD	DD	NDD
Enjoyment (music)	Social support	Suicidality	Intrusions	Positive/ negative life events	Medical investigation				Personality functioning questionnaire	Did you get into a physical/ verbal fight?	Menstruation cycle
Suicidal thoughts			Avoidance	Quit smoking					suicidality		

	Hyperarousal	Therapy sessions		self-harm
	Startling			
	PCL/PSS			

Supplement B

All items, unless otherwise noted, are answered on vertical 7-point Likert scales with the following anchors: Not at all, 2, 3, 4, 5, 6, Extremely.

Supplement B1. Momentary items.

Please indicate to what extent you feel the following mood states and physical sensations at this moment:

- Sad
- Guilty
- Happy
- Hopeless
- Anxious
- Stressed
- Overwhelmed
- Angry
- Calm
- Energetic
- Lonely
- Paranoid
- In pain
- Dizzy
- Nauseous
- Trembling
- Like my heart is racing

Please indicate to what extent you agree with the following statements:

- At this very moment, I look forward to completing the activities that I planned for later
- At this very moment, I am satisfied with myself
- At this very moment, I am satisfied with my physical appearance
- At this very moment, I experience cravings

If the question “At this very moment, I experience cravings” is answered with anything other than “Not at all”. The following question is triggered:

- What do you crave? (You can select more than one answer.)

With the following answer options: Food, alcohol, cigarettes, E-cigarettes, Cannabis (hashish/marijuana), Cocaine, Ecstasy/MDMA, Psychedelics (magic mushrooms/truffles), Other.

- What are you doing right now?

With the following answer options: Eating, Working/Studying, Physical activity, Household tasks, Resting, Using social media, Watching a movie/series, Hobbies, Hanging out with friends, Personal care, On my way to somewhere, Something else.

- How much do you enjoy what you're doing right now?

- How many people are you with right now?

With the options: 0, 1, 2, 3, 4, 5, 6 or more.

If this question is answered with anything other than "0" the following two questions are triggered:

- Who are you with? (You can select more than one answer.)

With the following answer options: Family, Partner, Friend(s), Colleague(s)/Classmate(s), Stranger(s).

- How much do you enjoy their company?

- *Please indicate what you ate since the last beep. (You can select more than one answer.)

With the following answer options: Nothing, Healthy snack, Unhealthy snack, Healthy meal, Unhealthy meal.

If this question is answered with anything other than "Nothing" the following question is triggered:

- Did you experience a loss of control while eating?

- *Did you smoke since the last beep?

With the options “Yes” and “No”. This question is only triggered if the participant states at baseline that he or she smokes.

Please indicate to what extent you agree with the following statements:

- **Since the last beep I felt like I was in control
- **Since the last beep I was able to concentrate
- **Since the last beep I have been worrying
- **Since the last beep I like how people are treating me
- **Since the last beep I did or said something without thinking first

Supplement B2. Daily items.

Morning items, asked in the first beep of the day together with the momentary items:

Note. Items in the momentary survey with an asterisk (*) are phrased “since the last beep” in the momentary survey, but “since you woke up” in the morning survey. Items in the momentary survey with an asterisk (**) are phrased “Since the last beep” in the momentary survey, but “Since I woke up” in the morning survey.

- Did you have a nightmare last night?

With the options “Yes” and “No”.

If this question is answered with “Yes” the following question is triggered:

- How distressing was the nightmare?

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not distressing at all, 2, 3, 4, 5, 6, Extremely distressing.

- How satisfied are you with last night's sleep?

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not satisfied at all, 2, 3, 4, 5, 6, Extremely satisfied.

- How rested do you feel?

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not rested at all, 2, 3, 4, 5, 6, Extremely rested.

- Did you use any of the following substances yesterday?

With the following answer options: Alcohol, Cigarettes, E-cigarettes, Cannabis (hashish/marijuana), Cocaine, Ecstasy/MDMA, Psychedelics (magic mushrooms/truffles), Other drugs; No, I did not use any of these substances.

Evening items, asked at a fixed time late in the evening <u>separately from the momentary items</u>:

Please indicate to what extent you agree with the following statements:

- Today I felt like I could count on my friends and/or family for support.
- I was able to handle today's challenges.
- Today, did you avoid any of the following? (You can select more than one answer.)

With the following answer options: Unpleasant interactions with somebody, Certain places or situations, Negative or hurtful thoughts, Daily activities, Scary or stressful objects or animals, Scary or stressful places, Scary or stressful activities, Pain-inducing activities, Unpleasant memories, Physical intimacy, No, I did not avoid any of these.

For <u>each</u> of the <u>selected</u> options a question was triggered that looked like this:

- To what extent did you avoid [selected option] today?

Indicate if you engaged in any of the following activities today and, if so, to what extent

- I intentionally hurt myself
- I watched porn
- I checked my body
- I was obsessively thinking
- I felt the compulsions to do certain things
- I looked for information on the internet regarding my health
- I had a conflict
- I vomited on purpose
- I used laxatives

- In general how was your day?

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not good at all, 2, 3, 4, 5, 6, Extremely good.

- Today my sexual desire/drive was…

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not strong at all, 2, 3, 4, 5, 6, Extremely strong.

- Did you take your medication today?

With the options “Yes” and “No”. This question is only triggered if the participant states at baseline that he or she is taking medication for a mental health problem.

- Did you visit a healthcare professional today?

With the options “Yes” and “No”.

Supplement B3. Weekly items.

Triggered every 7 days at a fixed time.

Please answer the following questions thinking about the last 7 days:

- How many times did you engage in any sexual behavior? (alone or with someone)

With the following answer options: 0, 1, 2, 3, 4, 5, 6+.

- How satisfied are you with your sex life?
- Did you wish to die or disappear during this week?

Answered in a vertical 7-point likert scale with the following options going from top to bottom: Not at all, 2, 3, 4, 5, 6, A lot.

- Does your life have a clear meaning?

Chapter 3

Validation of a transdiagnostic psychopathology EMA protocol in a university students sample.

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Abstract:

Ecological Momentary Assessment (EMA) collects real-time data in daily life, enhancing ecological validity and reducing recall bias. An EMA questionnaire that measures symptoms and transdiagnostic factors was recently developed with network modeling purposes. This study examines this EMA protocol's (1) subjective experience (e.g., burden, item clarity, survey frequency adequacy, etc), (2) compliance, dropout, and predictors thereof, (3) the variability of EMA items across and within participants, and (4) the relations between EMA items and baseline standardized psychopathology questionnaires. University students (n = 262 M_{age} = 21.9, 84.8% females, 17.2% Dutch) completed eight daily momentary surveys (with the first including morning survey), an evening survey, and a weekly survey during a 4-week EMA protocol. Additionally, a concluding survey examined participants' subjective experiences. Perceived burden was 3.40 on a 7-point scale, and people with higher levels of psychopathology found it more burdensome and more difficult to complete. 67% of the surveys were completed and 16% of the participants dropped out. Baseline psychopathology was not significantly associated with dropout or compliance. Moreover, surveys triggered in later study days, during the weekend, longer surveys, and surveys with lower financial reward were more likely to be missed. Between-subjects and within-subjects variability and correlations with baseline psychopathology varied across EMA items, with most EMA-items showing sufficient within-individual variability for network modeling purposes and showing correlations across all types of psychopathology and transdiagnostic factors. The results suggest that the collection of intensive time-series data is feasible, and data quality and characteristics match requirements of different network models.

The network approach to psychopathology is an alternative framework to the medical model for understanding mental disorders (Borsboom, 2017). This approach states that the symptoms of mental disorders are not provoked by an underlying common cause located in the brain, as the medical model proposes (Bruce, 2009; Deacon, 2013). Instead, it posits that a system of dynamic interactions between symptoms – within an individual – constitutes a mental disorder (Borsboom, 2017) Recently, it was proposed to not only include symptoms in these networks, but also other relevant variables, such as contextual circumstances and certain behaviors like the activities an individual engages in or social interactions (Roefs et al., 2022). As such dynamic interactions occur between symptoms across diagnostic categories (Cramer et al., 2010) the network approach is transdiagnostic in nature.

Taking an individual transdiagnostic perspective requires examining how mental health phenomena evolve over time within an individual. Ecological Momentary Assessment (EMA) is commonly used to assess these phenomena in psychopathology (Shiffman et al., 2008). EMA encompasses a variety of methods (e.g., time-contingent or event-related sampling) to collect repeated real-time data in participants' natural environments (Shiffman et al., 2008), mostly using smartphones for data-collection. EMA studies use items from questionnaires and surveys that were developed for laboratory or retrospective survey studies (Cloos et al., 2023; Schreuder et al., 2020). This is not necessarily problematic, but the psychometric qualities and subjective experience of any EMA protocol and items must be carefully examined.

The current study investigated characteristics of a transdiagnostic EMA-protocol that was developed based on input from expert clinicians, with the goal of enabling data-collection for the estimation of transdiagnostic intra-individual networks (Jover Martínez, Lemmens, Fried, & Roefs, 2024). Specifically, the present study examined: (1) the subjective experience of participants in the EMA-protocol, (2) overall compliance, momentary predictors of compliance (predictors that change from moment to moment), dropout, and the predictors of both compliance and dropout, (3) the within-subjects and between-subjects variability of EMA items, and (4) the relationship between the EMA-items and standardized questionnaires of psychopathology.

Goal one. Subjective experience EMA protocol

The experience of participants – such as the experienced burden- in EMA studies is known to influence the quantity and quality of data (Eisele et al., 2022; Moskowitz &

Young, 2006; Stone et al., 2003). For example, longer questionnaires are related to higher momentary and retrospectively reported burden, but questionnaire frequency is not (Eisele et al., 2022). Given the paucity of evidence available on the burden of EMA studies, and considering that it can affect data quality, dropout, and compliance, assessment of experienced burden in EMA studies is essential. Moreover, other subjective experiences, such as whether the study period is a good representation of participants' lives, how difficult it is to complete the surveys, how adequate the frequency of the surveys is, how clear the questions are, or how difficult it is to know the answer to the items, and to what extent participation impacts their daily lives are investigated in the current study as well.

Goal two. Overall compliance, momentary predictors of compliance, dropout and related factors

In addition to burden, there are other variables that can influence compliance and dropout (i.e., leaving the study before completion). For example, personal variables such as gender or age, study variables such as length of questionnaire, and momentary predictors such as the participant's momentary mood. Researchers have mostly explored compliance at the study level, focusing on personal (e.g., gender, age, mental health diagnosis, etc), design (e.g., frequency of assessment, length of surveys, length of study, etc), and time characteristics (e.g., study days, time within a day, weekdays, etc). Regarding personal characteristics, compliance of female participants is typically higher than of male participants (Eisele et al., 2022; Vachon et al., 2019), but there are no gender differences in dropout (Wrzus & Neubauer, 2023). If and how a clinical diagnosis affects compliance is less clear, with studies providing mixed findings (Jones et al., 2019; Rintala et al., 2020; Vachon et al., 2019). However, it seems like neither psychological nor physical health conditions are related to dropout (Wrzus & Neubauer, 2023). Age does not seem to be significantly related to compliance either (Rintala et al., 2020; Vachon et al., 2019).

Regarding characteristics of the study design, research has not found relations between variables such as study length or compliance reinforcement (i.e., rewarding participants more when they are more compliant) and compliance or dropout (Jones et al., 2019; Vachon et al., 2019; Wrzus & Neubauer, 2023). Other design characteristics can impact compliance. Longer questionnaires are associated with lower compliance rates (Eisele et al., 2022), and longer between-surveys intervals and higher incentives with higher compliance rates (Vachon et al., 2019; Wrzus & Neubauer, 2023). Moreover, an experimental study comparing different EMA protocols found that all dropouts were in the condition with longer surveys and higher assessment frequency (Eisele et al., 2022). However, results on the relation between assessment frequency and compliance are mixed. Most studies find no significant relation between survey frequency and compliance (Eisele et al., 2022; Jones et al., 2019; Stone et al., 2003), but in one study a negative relation was found (Vachon et al., 2019). Finally, regarding time characteristics, compliance is consistently lower on later study days (Eisele et al., 2022; Rintala et al., 2019, 2020). The findings regarding specific weekdays, or specific times within a day are mixed and inconclusive (Rintala et al., 2019, 2020; Vachon et al., 2019).

Studying momentary predictors of compliance- predictors of compliance that change from moment to moment- is less common. One study found that being outside of home at the time of a survey, feeling disturbed by a survey, taking medication, and responding to a survey on later study days reduced the likelihood of responding to a specific survey (Rintala et al., 2020). Interestingly, deviation of an individual's mood from their mean, stress-related variables, and physical state variables were not significantly related to the likelihood of answering a survey (Rintala et al., 2020). Finally, certain weekdays, and hours within a day were related to the likelihood of responding to a survey (Rintala et al., 2020). This type of information can be used to optimize compliance in EMA studies, but "little is still known about factors that influence compliance." (Rintala et al., 2020, p.1). Therefore, investigating our protocol's compliance rates, along with predictors thereof can determine how feasible it is, and provide information on how to improve it.

Goal three. Within- and between-individual variability

Another consideration for EMA studies is that items need to be specifically designed, for these purposes. EMA studies in psychopathology have frequently used standard questionnaires, which were designed for laboratory or retrospective studies. The tacit assumption was that these questionnaires would also be able to capture the momentary fluctuations of interest (Schreuder et al., 2020), which is one of the core assumptions of EMA studies (Schreuder et al., 2020). However, it is questionable if this assumption is always valid. In case of not meeting this assumption, among others, available statistical models will not be able to capture relations between variables due to lack of variability. Therefore, studying the variability of the EMA items is crucial.

Goal four. Relationship between EMA items and standardized questionnaires of psychopathology

Moreover, EMA questionnaires need to have construct validity (Cronbach & Meehl, 1955). Here we focus on convergent and divergent validity. Convergent validity is achieved when the measure of interest is correlated to other measures that assess the same or similar constructs whereas divergent validity is achieved if the measure of interest is uncorrelated with dissimilar measures. Therefore, for our research purposes, items included in an EMA questionnaire should reflect the entire range of psychopathology. Moreover, the different items should be associated with specific subscales of standardized questionnaires of psychopathology, and uncorrelated to other subscales (Schreuder et al., 2020). For example, an item that captures body image issues should be highly correlated with subscales that measure eating disorders, but uncorrelated with subscales that measure, for example, interpersonal problems.

The Present Study

With this in mind, the present study had four objectives. First, the relations between the subjective experience of participating in the EMA protocol and personal variables, such as level of psychopathology, gender, and diagnosis were studied. Second, overall compliance, and its relation to personal characteristics, such as psychopathology, gender, and past diagnosis, were studied. Moreover, momentary compliance was studied in relation to time variables (i.e., study day, and weekend), study variables (i.e., survey type), and personal variables (i.e., positive and negative affect, and missingness at the previous time point). Furthermore, dropout was studied in relation to gender, diagnosis and level of psychopathology. Third, the within- and between-individual variability of the EMA items were investigated. Fourth and finally, the relationships between the EMA items and standard questionnaires of psychopathology were examined.

Method

Transparency and Openness

The reported analyses were not preregistered, but the study was pre-registered on AsPredicted (https://aspredicted.org/ej6jp.pdf) with registration number 78277. Data are available upon reasonable request. Study materials, and code used in this analysis are publicly available at the Open Science Framework repository and can be accessed at https://osf.io/hq6fn/. All analyses were performed using R 4.2.2 (R Core Team, 2016).

Participants

Participants were university students of Maastricht University, Leiden University, or the University of Amsterdam (UvA). They needed to have sufficient English proficiency and own a smartphone. The reward for participating consisted of up to €75 in vouchers, or up to €60 in vouchers and two research credits (one research credit equals one hour of work or €7.5) depending on their compliance. If a participant chose the €75 in vouchers option, this participant would get €10.63 for filling in the baseline, €0.26 for each momentary survey, and €0.49 for any survey that was not momentary. For the €60 in vouchers option, the baseline had the same reward, each momentary item added €0.20, and the other surveys added €0.38. Moreover, the research credits varied based on compliance: 0.5 credits for 0-25%, 1 credit for 26-50%, 1.5 credits for 51-75%, and 2 credits for 76-100%.

A total of 322 participants showed interest in the study, but 34 did not complete the baseline questionnaire. Of the remaining 288 participants, twenty-six participants (9.1%) did not start the EMA measurement protocol, leaving a total sample of 262. All analyses were performed with the 262 participants who began the EMA protocol, except the dropout analysis which included the 288 participants who completed the baseline questionnaire. The mean age of the participants was 21.9 years (SD = 2.9), 84.8% were female (n = 218) and came from different countries (i.e., 19.5% German, 17.2% Dutch, 7.3% Italian, 3.4% British, 3.4% Chinese, 3.4% American, 3.1%Spanish, 2.7% Belgian, 2.3 Polish, 2.3 Romanian, 1.5% Danish, 1.5% Hungarian, and 32.4% other nationalities). 24.4% (n = 64) had received a diagnosis of a mental disorder at some point in their lives, and four participants were receiving some type of treatment for a mental disorder at the beginning of the study. The study was approved by the ethical review board of the Faculty of Psychology & Neuroscience of Maastricht University.

Procedure

Participants could join the study between March 2nd, 2022 and May 31st, 2022. The study was advertised on university advertisement boards, on a 'research credit' platform for students (i.e., SONA), and on social media (Instagram and Facebook). The advertisements contained a link or a QR code that directed participants to the study website, where they were informed about the study and provided informed consent. The study consisted of a screening and a monitoring phase. To start the study, participants were instructed to download the app "Ethica/Avicenna" from EthicaData / Avicenna Research (https://avicennaresearch.com/), which was used for data collection.

Screening phase

First, participants completed an online screening in Ethica/Avicenna to check the inclusion criteria, and to provide some personal information (e.g., name, phone-number, and email). The following day, participants received a set of questionnaires of psychopathology (see further), which had to complete in four days. On the fifth day, a practice day, structured like a real study day, was completed to familiarize themselves with the procedure. On one of the following four days, participants received an evaluation phone call to verify that they met the inclusion criteria, and that the EMA protocol was clear. The following day, the monitoring phase began. Participants could only start if they completed the online screening, the baseline questionnaires, the practice day, and the evaluation phone call. For a summary of the screening phase timeline, see Figure 1.

Monitoring phase

The monitoring phase consisted of 28 days on which participants were prompted several times per day to answer surveys on their smartphone. Each day, they received a morning survey, 8 momentary surveys throughout the day, and an evening survey. In addition, at the end of each week, they received a weekly survey. The day after the last EMA-survey, participants received a survey on their experience of the study. The morning, evening, and weekly surveys were rewarded 50% more than the momentary surveys. The participants received emails approximately every 7th day updating them on how much reward they would earn if they kept answering at their current pace. If participants were not compliant, they were called to find out why, and if a problem was identified, a solution was sought.

Measurements

A thorough overview of all measures, including instructions, scoring, means and variability metrics for the EMA items, and Cronbach's alphas for the baseline measures is available online at https://osf.io/hq6fn/.

Baseline assessment

Participants first completed some questions about demographic and personal characteristics (e.g., gender, employment, age, nationality, etc). Next, participants completed 15 standard questionnaires of psychopathology: 11 about a specific type of psychopathology, and four about transdiagnostic factors. See supplementary table 3 for an overview and the minimum and maximum score of each questionnaire.

Brief Symptom Inventory (BSI). The BSI is a 53-item psychological self-report symptom scale (Derogatis & Melisaratos, 1983), scored on a 5-point Likert scale going from 0 (Not at all) to 4 (Extremely). It measures nine psychopathology dimensions: somatization, obsession–compulsion, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, and psychoticism. Each scale score is computed as the mean of the items that make up the scale. A general BSI score was computed as the average of all items, with higher scores indicating greater severity of symptoms (de Beurs & Zitman, 2006).

Depression Anxiety Stress Scale (DASS-21). The DASS-21 is a self-report scale composed of three seven-item subscales scored scored on a 4-point Likert scale going from 0 (did not apply to me at all) to 4 (applied to me very much, or most of the time). The DASS-21 subscales measure depression, anxiety, and stress (Lovibond & Lovibond, 1995). To calculate the subscales scores, the seven items of each subscale are summed, and the sum is multiplied by two. A higher score on a scale indicates a greater level of the measured state.

Diagnostic and Statistical Manual of Mental Disorders (DSM-5) Adult Attention Deficit and Hyperactivity Disorder (ADHD) Self-Report Screening Scale (ASRS). The ASRS is a six-item self-report scale that measures the severity of DSM-5 symptoms for the diagnosis of ADHD scored on a 5-point Likert scale going from 0 (never) to 4 (very often), with higher scores indicating greater symptom severity (Ustun et al., 2017).

Autism Spectrum Quotient (AQ-10). The AQ-10 is a 10-item self-report scale that measures the expression of Autism-Spectrum traits (Allison et al., 2012) scored on a 4-point Likert scale with 1 representing “Definitely disagree”, and 4 representing “Definitely agree”. To compute the AQ-10 total scored, each item above 2 is counted. Higher quotient scores indicate greater autism-spectrum expression. For an explanation of how the quotient is calculated see Allison et al. (2012).

Eating Disorders Examination Questionnaire-Short (EDEQ-S). The EDEQ-S is a 12-item self-report scale designed to assess range, frequency, and severity of behaviours related to eating disorders diagnoses (Gideon et al., 2016) scored on a 4-point Likert scale going from 0 (0 days or not at all) to 3 (6-7 days or markedly). A sum score is used to summarize the scale, with higher scores indicating greater eating pathology.

Post-Traumatic Stress Disorder (PTSD) Checklist for DSM-5 (PCL-5). The PCL-5 is a 20-item self-report scale that assesses the 20 DSM-5 symptoms of PTSD (Blevins et al., 2015). The PCL-5 is answered on a 5-point Likert scales going from 0 (not at all), to 4 (extremely). A severity score is obtained by summing the items’ scores, with higher scores indicating greater PTSD symptom severity.

Sexual Dysfunction Questionnaire (SDQ). The SDQ is a 19-item self-report scale that assesses sexual problems in psychiatric patients (Infrasca, 2011) scored on a 5-point Likert scale going from 1 (never) to 5 (always). The total score is a sum score of all the items' scores, with higher scores indicating a higher likelihood of experiencing sexual problems.

Insomnia Severity Index (ISI). The ISI is a seven-item self-report scale that measures sleeping difficulties (Bastien, 2001) scored on a 5-point Likert scale going from 0 (none or very dissatisfied) to 4 (very severe or very satisfied). The seven items are summed up, and higher sum scores indicate greater sleeping difficulties.

Alcohol Use Disorders Identification Test (AUDIT). The AUDIT is a 10-item self-report scale that screens for risky or hazardous alcohol use (World Health Organization, 2001). The first eight items are assessed on 5-point Likert scales. Of those eight, the first item goes from "Never" to "4 times a week or more often", the second goes from "1-2" to "10 or more", and the other six go from "Never" to "Daily or almost daily". The last two items are assessed in a 3-point scale going from "Never" to "Yes, during the last year". The items' scores are added up to a total score, with higher scores indicating higher alcohol dependence.

Drug Use Disorders Identification Test (DUDIT). The DUDIT is an 11-item self-report scale that screens for drug-related problems (Berman et al., 2016). The first nine items are assessed on 5-point Likert scales. Of those nine, the first two items go from "Never" to "4 times a week or more often", the third goes from "0" to "17 or more", and the last six items go from "Never" to "Daily or almost daily". The last two items are assessed on 3-point Likert scales that go from "Never" to "Yes, over the past year". The items' scores are added up in a total score, with higher scores reflecting higher drug dependence.

Levels of Personality Functioning Scale Brief Form (LPFS-BF). The LPFS-BF is a 12-items self-report scale that measures presence and general severity of personality pathology scored on a 4-point Likert scale going from 1 (completely untrue) to 4 (completely true). The items are averaged, and higher scores reflect greater severity of personality pathology (Weekers et al., 2019).

Brief Fear of Negative Evaluation Scale (BFNES). The BFNES is a 12-item self-report scale of a person's tolerance for the possibility they might be judged disparagingly or hostilely by others (Duke et al., 2006) scored on 5-point Likert scales going from 1 (not at all characteristic of me) to 5 (extremely characteristic of me). A total score is calculated by adding the scores of the items, with higher scores indicating greater distress related to social situations.

Dichotomous Thinking Inventory (DTI). The DTI is a 16-item self-report scale that measures black-and-white cognitive thinking style (Byrne et al., 2008) scored on a 4-point Likert scale going from 1 (not at all true of me) to 4 (very true of me). The DTI consists of two subscales: one six-item subscale measuring dichotomous thinking related to food, eating, dieting, and weight, and a 10-item subscale measuring general dichotomous thinking. Moreover, a global measure is computed by summing all items. On all these scales, higher scores indicate a greater tendency to think in black or white terms.

Self-Control Questionnaire (SCQ). The SCQ is a 36-item self-report scale that measures an individual's ability to control impulses, modulate cognitive and affective processes, and intervene on undesirable behavioral tendencies while refraining from their execution (Brandon et al., 1990) scored on a 5-point Likert scale going from 1 (not at all like me) to 5 (very much like me). The total score is computed by summing up the items, with higher scores indicating a higher degree of self-control.

Ten-Item Personality Inventory (TIPI). The TIPI is a 10-item self-report brief version of the Big-Five personality dimensions (Gosling et al., 2003) scored on a 7-point Likert scales going from "disagree strongly" to "agree strongly". Pairs of items represent each of the Big-Five elements: extraversion, agreeableness, conscientiousness, emotional stability, and openness to experience. Averages of these item pairs are used to measure each of the Big Five elements, with higher scores reflecting higher levels of the measured personality element.

EMA protocol

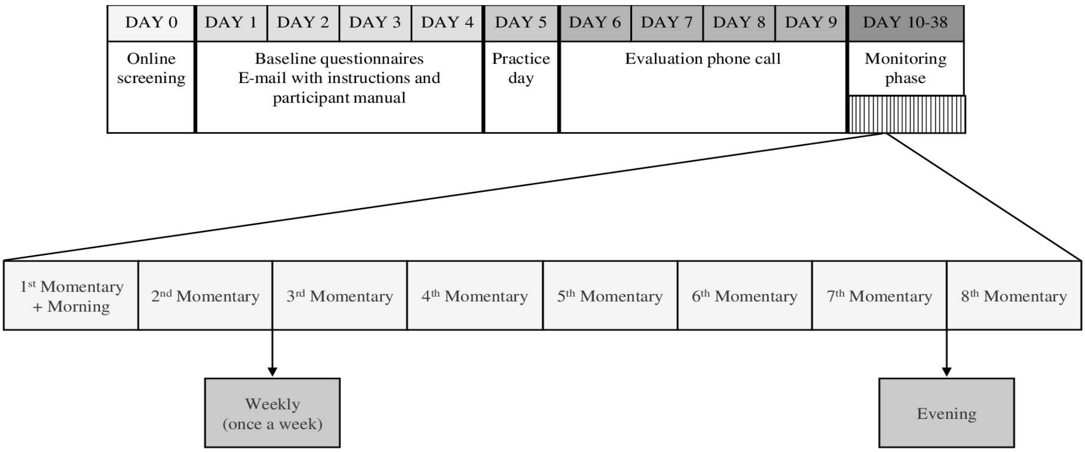
Details of the EMA protocol has been described elsewhere (Jover Martínez, Lemmens, Fried, & Roefs, 2024) and will only be summarized here. The transdiagnostic EMA protocol covered the whole spectrum of psychopathology and included four types of surveys: a morning survey (five items), a momentary survey (up to 35 items; eight times per day), an evening survey (up to 27 items) and a weekly survey (four items). See Figure 1 for a graphical representation of the EMA protocol. The morning survey coincided with the first momentary survey of the day. Some items were not triggered for everyone (e.g., Did you smoke since the last beep?), and other items were triggered based upon the answer to a previous item (e.g., "What do you crave?" was triggered only if the answer to "At this moment, I experience cravings" was not "Not at all"). Therefore, the specific number of items could differ across people and measurement moments. Most items were quantitative and were answered on 7-point Likert scale. The meaning of the different scores varied depending on the question. The questionnaires also included qualitative items asking about for example company, location, substance use, etc.

Momentary surveys were triggered semi-randomly in time windows of 1:37:30 minutes, following a normal distribution to increase the likelihood of surveys being triggered in the middle of the time window. The evening and weekly surveys were triggered at a specific moment to increase compliance (Eisele et al., 2022). The morning and evening surveys expired in 45 minutes, the weekly survey expired in 12 hours, and the momentary surveys in 20 minutes. The time at which measurements started each day was adapted to participants' usual waking time. Participants were asked whether they usually woke up before 9 AM, between 9 and 11 AM, or after 11 AM. Depending on the answer, the first survey (i.e., morning and first momentary survey) was triggered between 07:30:00 AM and 09:07:30 AM, 09:07:30 AM and 10:45:00 AM, or 10:45 AM and 12:22:30 PM respectively. Subsequently, the seven remaining momentary surveys were triggered within the semi-random time windows specified above. The evening surveys were triggered between 08:30:00 PM and 9:30:00 PM, 9:30:00 PM and 10:30:00 PM, or 10:30:00 PM and 11:30:00 PM depending on each participant's waking preference. The weekly survey was triggered at 12:00:00 PM for everybody.

After the last survey of the monitoring phase was completed, participants received a survey about their subjective experiences participating in the EMA protocol. This survey consisted of seven items, assessed on 7-point Likert scales. The survey assessed whether participants thought the study period was a good representation of their lives, how difficult it was to complete the surveys, how burdensome the study was, how adequate the frequency of the surveys was, how clear the questions were, how difficult it was to know the answer to the items, and how much participation impacted on their daily lives. For an overview of this survey see Table 2.

Figure 1.

Study timeline.



Note. The lower part of the figure represents a single day of the monitoring phase. The evening and weekly phase are indicated with an arrow because they were triggered at a fixed time. The weekly survey was triggered only once a week.

Analysis

Goal one. Subjective experience EMA protocol

Intercorrelations between the subjective experience survey items and scores on the general Brief Symptom Inventory's (BSI) were computed. Additionally, the differences between participants who had received a diagnosis and those who had not, and between genders, in the evaluation-of-study survey questions were analyzed using independent samples t-tests.

Goal two. Overall compliance, momentary predictors of compliance, dropout and related factors

The relationship between overall compliance and gender, past diagnosis, survey type, different weekdays, was studied by paired samples t-tests and one-way within-subjects ANOVAs. Finally, the relationship between compliance and psychopathology was examined by correlation analysis.

Compliance at the momentary level was examined in a multilevel logistic regression model with the lme4 package (Bates et al., 2015) using whether a survey was answered or not as the dependent variable. Table 1 includes a summary of the predictors. Random intercepts were included per participant, and the predictors were first analyzed with univariate models and then with a multivariate model that included all predictors simultaneously. Positive affect was conceptualized as the average of happy, calm, and energetic, and negative affect as the average of sad, guilty, hopeless, anxious, stressed, overwhelmed, angry, lonely, and paranoid.

To study dropout, a logistic regression model was used with dropout (0 = not dropout, 1 = dropout) as the dependent variable. A participant was considered a dropout if they did not start the last week of the EMA protocol. To predict dropout, the personal characteristics of table 1 (i.e., gender, diagnosis, and BSI score) and the average level of positive and negative affect were used as predictors. All variables were introduced in the model simultaneously.

Table 1.

List of predictors and coding for compliance at the momentary level.

Variable	Level	Type	Coding
Personal characteristics			
Psychopathology level (BSI score)	Person	Continuous	0-4
Age	Person	Continuous	18-33
Gender	Person	Dichotomous	0 = Male 1 = Female
Time variables			
Day number	Day	Continuous	1-28
Weekend	Day	Dichotomous	0 = Weekday 1 = Weekend
Design variables			
Survey type	Survey	Categorical	Dummy coded with

			momentary surveys as reference
Momentary variables			
Missed survey at t-1	Momentary	Dichotomous	0 = Answered survey 1 = Missed survey
PA at t-1	Momentary	Continuous	1-7
NA at t-1	Momentary	Continuous	1-7

Goal three. Within- and between-individual variability

The variability of the EMA items was studied by computing the between- and within-individuals variance and the Intra Class Correlation (ICC) of the quantitative items. The between-individuals variance for each item was computed by calculating the standard deviation of the participants' mean scores (collapsed over timepoints) on that item. The within-individual variance was computed by first calculating the standard deviation of each item per individual across timepoints, and then calculating the average standard deviation across participants for each item. The ICC was calculated by taking the between-individuals variance per item and dividing it by the sum of the within-individuals variance and the between-individuals variance. A higher ICC value reflects a higher proportion of between-individuals variance relative to within-individuals variance. That is, scores on that item varied more across people than within an individual.

The qualitative items needed a different analytical approach. The variances of the qualitative items were reflected by Shannon's entropy (Shannon, 1948). The range of Shannon's entropy can go from 0 up to $log_2(k)$, with k being the number of categories of the studied variables. In the case of dichotomous outcomes, the entropy coefficient can range from 0 to 1. An entropy coefficient of 0 represents no uncertainty of the outcome, which in our case translates to no variability. The formula to calculate Shannon's entropy is the following:

$$H(x) = -\Sigma P(x_i) log P(x_i)$$

Where $P(x_i)$ is the probability of an outcome, which is calculated by dividing the occasions that an event was present by the number of times that an event could have been present. The entropy of each qualitative item was calculated per participant, and then these entropy-values were averaged across participants for each item.

Goal four. Relationship between EMA items and standardized questionnaires of psychopathology

To study the relation of the EMA items to baseline measures of psychopathology, correlations were computed. Specifically, the mean levels of the EMA items across time were correlated with the scores on the subscales of the baseline questionnaires.

Results

Goal one. Subjective experience EMA protocol

Table 2 contains a summary of the associations between the subjective experience of the EMA protocol, BSI score (M = 0.81, SD = 0.57), gender, and diagnosis. People with higher levels of psychopathology perceived that the period of the study was a worse representation of their lives, and more burdensome. Moreover, completing all surveys, and knowing the answer to the questions was perceived as more difficult. Finally, the study was perceived as less influential on their day-to-day life for male (M = 5.35) than for female (M = 4.87) participants.

Goal two. Overall compliance, momentary predictors of compliance, dropout and related factors

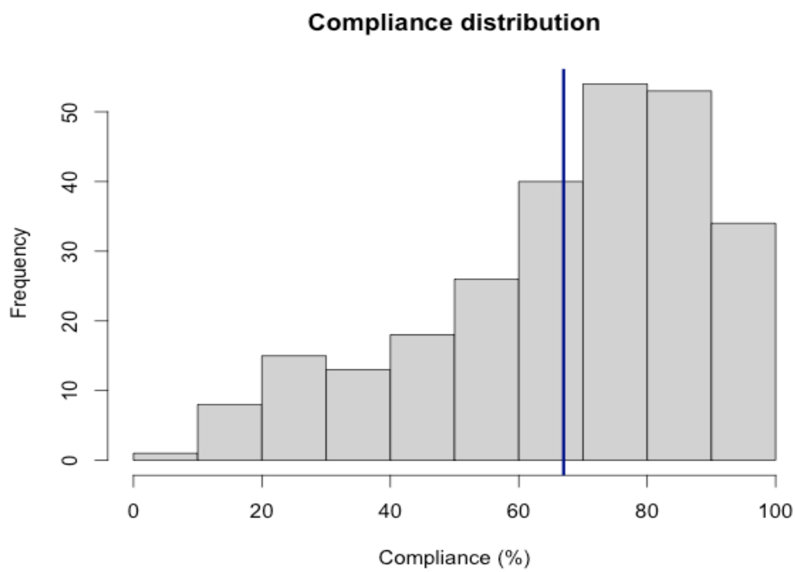
Compliance

Each participant received an average of 236 (SD = 57) surveys of which on average 162 were answered (SD = 65.7). The average compliance level was 67% (SD = 21.80) for the whole sample. Figure 2 shows the distribution of compliance per participant for the whole sample. Participants who answered at least 50% of the momentary surveys (n = 192), giving enough data to reliably estimate network models, had an average compliance of 75.77 (SD = 12.12). It took 14 minutes and 20 seconds on average to open a survey from the moment it was triggered. Compliance did not differ significantly between genders t(63.50) = 0.22, p = 0.83, or between people who had versus who had not received a diagnosis of a mental disorder in the past, $t(96.92) = 1.30$, $p = 0.19$. Finally, BSI score was not significantly correlated with compliance $r(260) = -0.04$, $p = 0.13$.

The compliance dropped across study days as displayed in panel A of Figure 3. Weekends had lower compliance than weekdays $t(256.00) = 4.65$, $p < 0.001$. Moreover, different days of the week had different levels of compliance $F(6,1476) = 13.28$, $p < 0.01$. Post-hoc pairwise t-tests showed that Mondays and Sundays were the days with lowest compliance (see panel B of Figure 3).

Figure 2.

Average compliance distribution.



Note. The blue line denotes the average compliance.

A within-subjects comparison with survey as factor revealed that different surveys also had different levels of compliance $F(3,741) = 321.86$, $p < 0.01$. The weekly survey had the highest compliance, followed by the evening survey, the morning survey, and finally the momentary survey. Follow-up paired-samples t-tests comparing each type of survey with all other types of survey revealed that compliance for every type of survey differed from all other types of surveys (see panel C of Figure 3).

Momentary predictors of compliance

Table 3 shows a summary of both the univariate and multivariate results of the multilevel logistic regression model predicting momentary compliance. Regarding time-related variables, surveys triggered on later study days, and surveys triggered during the weekend were significantly more likely to be missed. These effects remained significant in the multivariate model. Of the personal variables, higher positive affect and missing a survey at the previous time point significantly increased the likelihood of missing a survey, but these effects did not remain significant in the multivariate model. Concerning personal variables, neither gender, age, nor BSI score were significantly associated with the likelihood of missing a survey in either the univariate or the multivariate models. Finally, surveys that were more rewarded, contained fewer items and were triggered less frequently (i.e., morning surveys, evening surveys, and weekly surveys) were less likely to be missed than the momentary survey. However, the effect of the morning surveys did not remain significant in the multivariate model.

Table 2.

End of the study survey analysis.

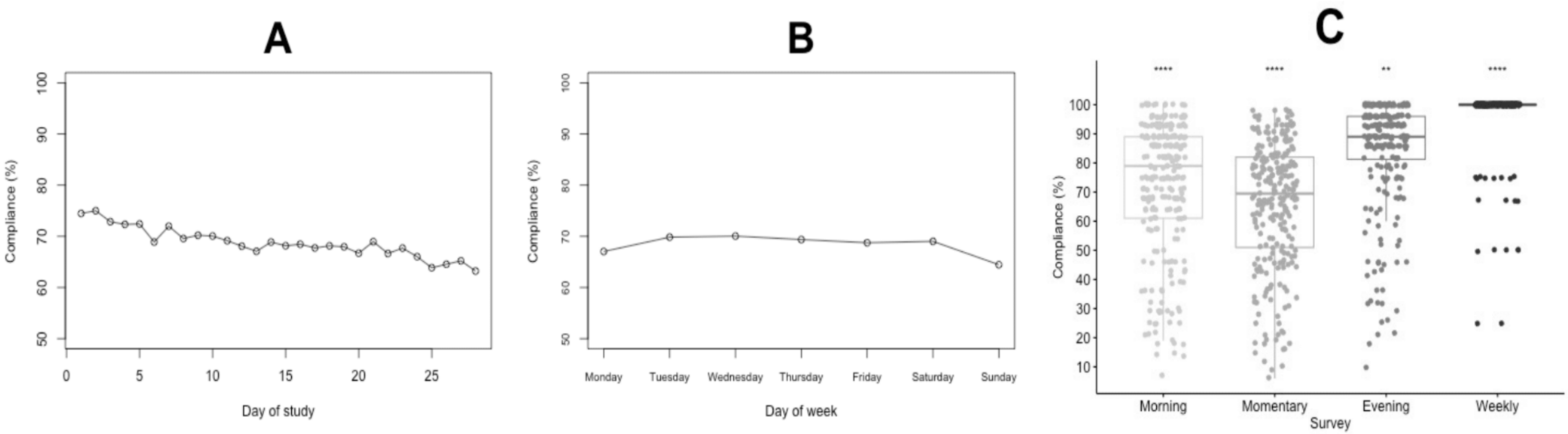
Item	Mean (SD)	Correlation with BSI	Gender	Diagnosis
In the past 4 weeks, to what extent was your day-to-day life representative of how it normally is? (1 = “An extremely bad representation”, 7 = “A perfect representation”)	5.06 (0.96)	$r(232) = -0.13$, $p < 0.05$	$t(49.75) = 1.75$, $p = 0.09$	$t(94.48) = 0.30$, $p = 0.76$
How did you experience filling out all notification surveys? (1 = “It was extremely difficult”, 7 = “It was extremely easy”)	3.85 (1.36)	$r(232) = -0.22$, $p < 0.001$	$t(49.75) = 0.65$, $p = 0.52$	$t(91.94) = 0.005$, $p = 0.99$
How burdensome was answering the notification surveys? (1 = “Not burdensome at all”, 7 = “Extremely burdensome”)*	3.50 (1.53)	$r(232) = 0.19$, $p < 0.01$	$t(55.36) = 0.04$, $p = 0.97$	$t(89.25) = 1.25$, $p = 0.22$

How was the frequency of the surveys (i.e. the number of times you were asked to fill in a survey every day)? (1 = “Extremely high”, 7 = “Extremely low”)*	2.89 (0.87)	r(232) =-0.04, p = 0.52	t(57.71) = 0.85, p = 0.40	t(76.27) = 0.004, p = 0.99
Were the questions clear? (1 = “Extremely unclear” 7 = “Extremely clear”)	5.46 (1.10)	r(93) =-0.14, p = 0.17	t(23.36) = 0.01, p = 0.99	t(72.14) = 1.20, p = 0.24
How difficult was it for you to know the answers to the questions? (1 = “Extremely difficult”, 7 = “Extremely easy”)	4.74 (1.31)	r(93) =-0.43, p < 0.001	t(29.26) = 0.60, p = 0.55	t(46.39) = 0.93 p = 0.36
How influential was your participation in this study on your day-to-day life? (1 = “Not influential at all”, 7 = “Extremely influential”)	4.96 (1.43)	r(232) =-0.08, p = 0.25	t(55.50) = 2.08, p = 0.04	t(86.04) = 0.25, p = 0.81

Note. r = correlation with levels of psychopathology. The 4th and 5th columns contain the results of the independent t-tests comparing the answers to each item between gender and diagnosis levels respectively. BSI = Brief Symptom Inventory. * = Item scale was the opposite tin the original questionnaire; for the current analysis the coding was reversed as described in the table.

Figure 3.

Average compliance per day of study, day of the week, and survey.



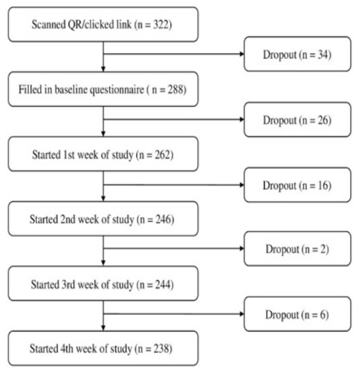
Note. Panel A: Average compliance per day of the study.Panel B: Average compliance per day of the week. Panel C: t-test comparisons of compliance for the different survey types. Each survey was compared to all other surveys. **** p-value < 0.0001, ** p-value < 0.01. The compliance of the morning survey also reflects the compliance of the first momentary survey of the day as these coincided. Each dot reflects 1 participant.

Dropout

Figure 4 shows a flowchart of the study's dropout. No significant associations between age (OR = 1.07, 95% CI [0.97-1.18]), gender (OR = 2.45, 95% CI [0.89-8.76]), diagnosis (OR = 0.74, 95% CI [0.33-1.59]), level of psychopathology (OR = 1.30, 95% CI [0.72-2.28]), and dropout were found, and the logistic model was not significant $\chi^2(4) = 4.85$, $p = 0.29$.

Figure 4.

Participants' dropout rates per study phase.



Goal three. Within- and between-individual variability

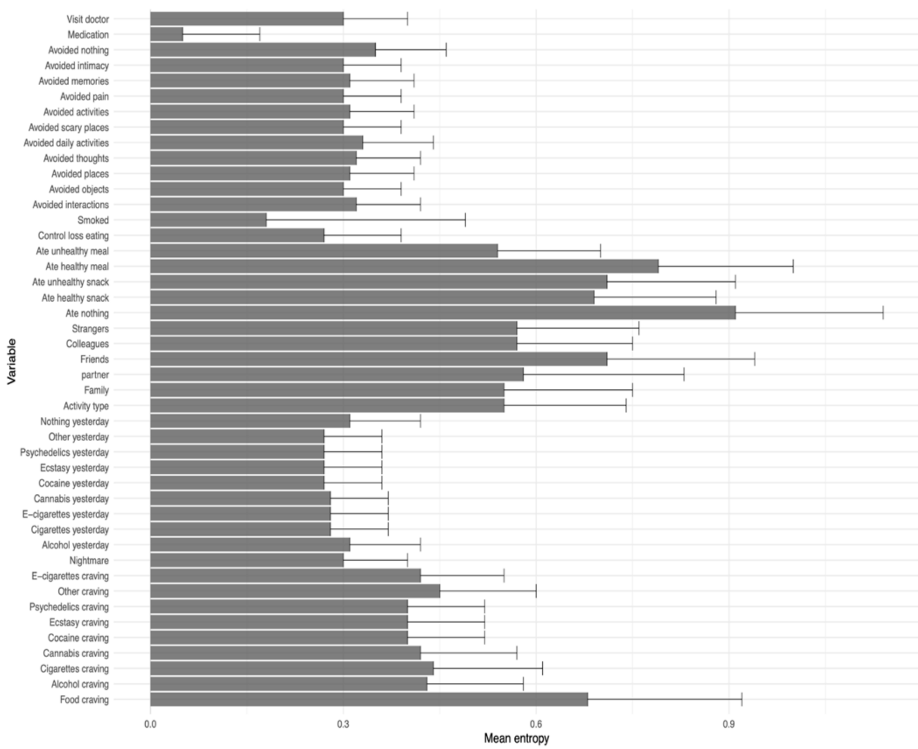
Figure 5 provides a visual representation of the items' scores on each metric (mean, between-individual variance, within-individual variance, and ICC) for the quantitative items. Supplementary table 1 contains the specific scores on these metrics. Note that standard deviations must be interpreted in the context of the scale that was used. A 7-point Likert scale with a mean of 4 and a standard deviation of 1 means that about 68% of the scores fall between 3 and 5, while 95% of the scores fall between 2 and 6.

The means of $std_{between}$ (M = 0.95; range: 0.30- 1.59), std_{within} (M = 0.91; range: 0.09- 2.42), and the ICC (0.57; 0.17- 0.93) show that items vary to some extent, and a bit more at the between-individuals level. Moreover, the ranges of values show that there is heterogeneity in variability across items. Items with higher std_{within} concerned contextual factors, such as number of people (1.66) enjoyment of company (2.42), and day appraisal (1.33). Lower std_{within} were found for items about extreme behaviors that were asked with lower time frequency, like use of laxatives (0.09), purging (0.13), and self-harm (0.17). Interestingly, the items with lowest std_{within} also had the lowest $std_{between}$, that is, use of laxatives (0.30), purging (0.42), and self-harm (0.38). Items with the highest $std_{between}$ were avoidance of objects (1.59), avoidance of intimacy (1.56), and sex satisfaction (1.56). In general, items about avoidance had high $std_{between}$. Finally, the items with low std_{within} and low $std_{between}$ had high ICCs (i.e., use of laxatives 0.93, purging 0.91, and self-harm 0.84).

Figure 6 shows a visual representation of the entropy scores of each item, and supplementary table 2 provides tables with the specific scores. The average entropy was 0.41, showing that on average, these items had low variability. However, some items scored above 0.5 on entropy, showing more variability. Similar to the quantitative items, contextual items such as food-related items, people-related items, and activity type had the highest entropy, showing more within-individual variability. The items with lowest entropies were smoking and taking medication. These items were just triggered for individuals who stated at baseline that they engaged in this type of behavior. Other items with low entropies concerned drug-consumption and control loss when eating. The mean standard deviation of the entropies was 0.14, showing that on average the items' entropies did not vary much across participants.

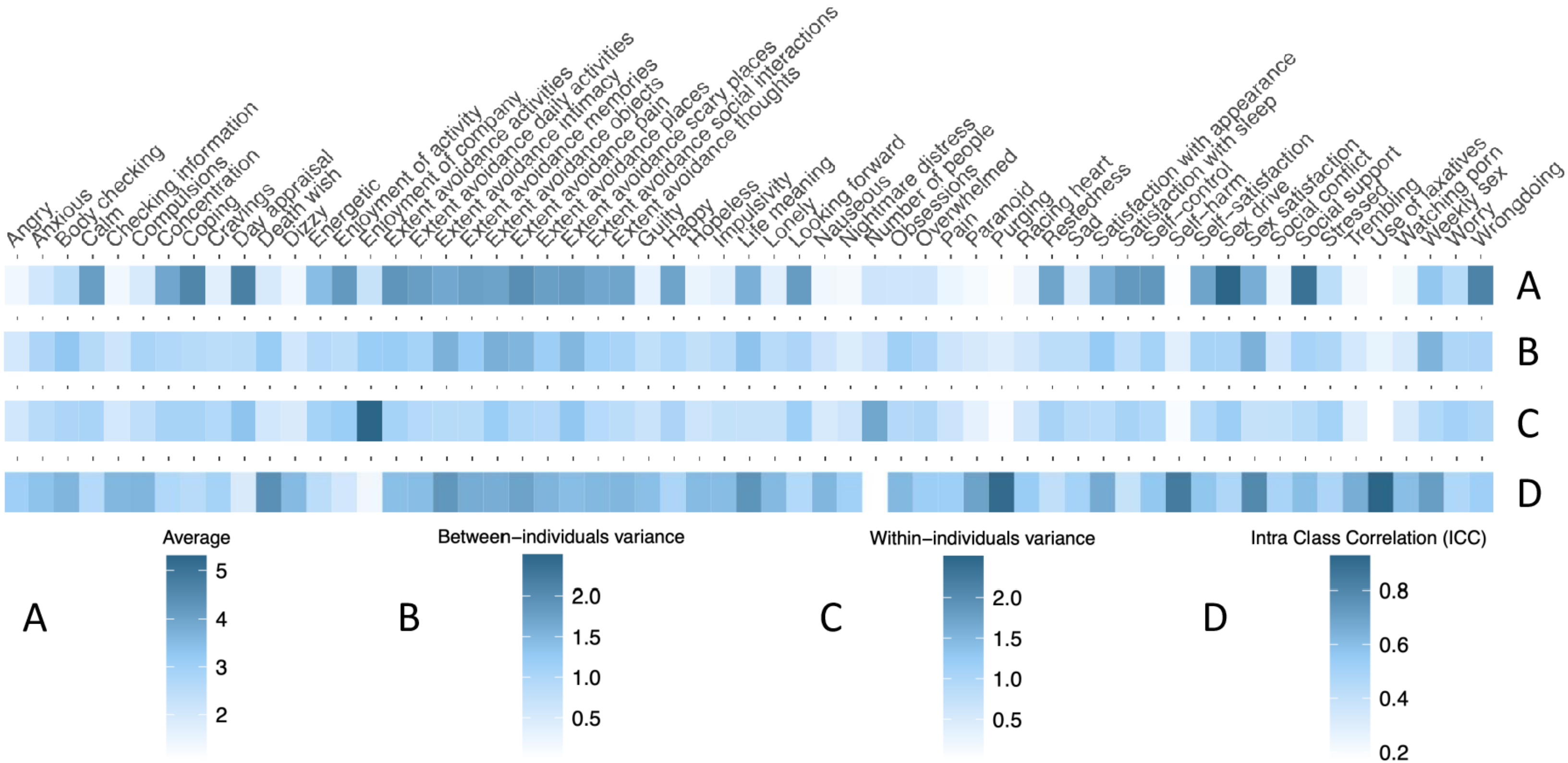
Figure 6.

Average entropy levels of qualitative items.



Note. Bars represent entropy levels and whiskers reflect one standard deviation

Figure 5. Visual representation of average and variability metrics of the quantitative items.



Goal four. Relationship between EMA items and standardized questionnaires of psychopathology

Table 3 provides descriptive values for the baseline questionnaires. A graph showing the correlations between the scores on the standard questionnaires of psychopathology and the scores on the EMA items averaged across time-points per individual is provided in Figure 7. In general, EMA items correlated with scores on most baseline measures (e.g., feeling rested, concentration, social support, and obsessions). Other EMA items were more disorder-specific, such as the avoidance items, sex-related items, or enjoying one's own company.

Notably some EMA items that were thought to be disorder-specific by clinical experts (Jover Martínez, Lemmens, Fried, & Roefs, 2024) were correlated with many disorder-related baseline measures. For example, body checking was included to capture eating disorder-related psychopathology, and checking information on the internet was included to capture anxiety-related psychopathology. However, these items were correlated with most other types of psychopathology.

The EMA items also correlated with scores on most transdiagnostic baseline measures (i.e. fear of negative evaluation scale (BFNES), dichotomous thinking (DTI), self-control (SCQ) and personality (TIPI)). Similar to the correlations with the psychopathology measures, the avoidance, sex-related, or items regarding enjoying the company of other displayed fewer correlations. While the direction of the correlations was the same for all the baseline measures, it was the opposite for the personality trait measures (i.e., extraversion, agreeableness, conscientiousness, emotional stability and openness to experience). For example, all the negative mood items correlate positively with all the baseline measures, but negatively with the personality measures, and this pattern is consistent across all EMA items.

Table 3.

Results of the momentary predictors of compliance.

	Individual predictor model	Multivariate model

Predictors	Odds ratio	CI	*p*	Odds ratio	CI	*p*
Intercept				0.17	0.04- 0.65	< 0.009
Study day	1.03	1.02- 1.03	< 0001	1.02	1.02- 1.02	< 0.001
Weekend	1.22	1.17- 1.27	< 0.001	1.09	1.02- 1.16	0.008
PA t-1	1.05	1.01- 1.08	0.005	1.04	0.997- 1.08	0.052
NA t-1	0.96	0.92- 1.01	0.108	0.98	0.93- 1.03	0.420
Missed survey t-1	2.06	1.97- 2.14	< 0.001	1.88	0.74- 4.76	0.185
Gender	0.87	0.60- 1.27	0.479	0.89	0.61- 1.29	0.533
Age	1.00	0.96- 1.05	0.976	1.02	0.97- 1.07	0.472
BSI score	1.15	0.90- 1.48	0.256	1.26	0.98- 1.62	0.068
Survey						
Morning	0.65	0.61- 0.69	< 0.001	0.82	0.60- 1.13	0.228
Evening	0.26	0.24- 0.28	< 0.001	0.17	0.15- 0.20	< 0.001
Weekly	0.03	0.02- 0.05	< 0.001	0.00	0.0001- 0.05	0.015
Random effects						

σ^2	3.29
τ_{00}	1.11
ICC	0.25

Discussion

In the current study, we thoroughly investigated the subjective experience and validity of a transdiagnostic psychopathology EMA protocol. Findings will be discussed per goal.

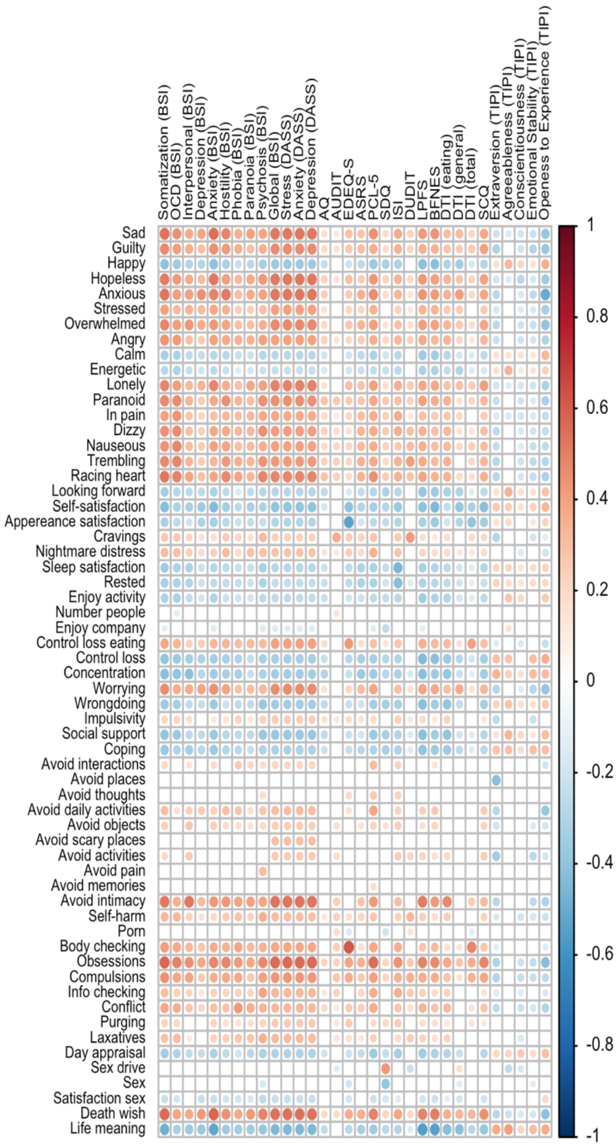
Goal one. Subjective experience EMA protocol

Participants' subjective experiences and the relations between such experiences and gender, receiving a diagnosis, and level of psychopathology were studied. On average, participants found the surveys neither easy nor difficult to complete, quite burdensome, and a bit frequent. Moreover, the items were perceived as clear, but it was neither easy nor difficult to know the answer. The study was perceived as a fairly good representation of their normal lives, and as being fairly influential on it. The burden scores in the present study were a bit higher than in a previous study (Eisele et al., 2022), possibly due to our different item-set and the longer duration of our study.

Male participants perceived the study period as less influential than did female participants. Several studies have found male participants to be less compliant, but not the current study (Eisele et al., 2022; Vachon et al., 2019). Note that the number of male participants in our study was limited. People who had received a diagnosis during their lives did not significantly differ from people without a diagnosis on burden-related variables. However, participants with higher levels of psychopathology perceived the study period as a worse representation of their lives, more burdensome, and found it more difficult to complete all surveys. They also found knowing the answer to the items more difficult. These findings align with studies that found that people with a mental health diagnosis are less compliant (Jones et al., 2019; Rintala et al., 2020; Vachon et al., 2019) because lower compliance rates in people with higher levels of psychopathology could be

Figure 7.

Correlations between EMA items averaged across time-points per individual (y-axis) and baseline questionnaires (x-axis).



Note. Color coding of strength and direction of correlations is displayed in the vertical bar on the right. BSI: Brief Symptom Inventory, DASS: Depression, Anxiety and Stress Scale, AQ: Autism Quotient, AUDIT: Alcohol Use Disorder Identification Test, EDEQ: Eating Disorder Examination Questionnaire, ASRS: Adult Attention Deficit and Hyperactivity Disorder, PCL: PTSD Check-List, SDQ: Sexual Dysfunction Questionnaire, ISI: Insomnia Severity Index, DUDIT: Drug Use Disorder Identification Test, LPFS: Levels of Personality Functioning Scale, BFNES: Brief Fear of Negative Evaluation Scale, DTI: Dichotomous Thinking Inventory, SCQ: Self-Control Questionnaire, TIPI: Ten Items Personality Inventory.

an attempt to reduce burden (Eisele et al., 2022; Stone et al., 2003). However, more research is needed on what specific diagnoses lead to a lower compliance, because certain diagnoses, such as Major Depressive Disorder, have been linked to higher compliance (Rintala et al., 2020). Considering that EMA studies will always have some impact on participants, it is concluded that the implemented EMA protocol's burden was acceptable. Future research with populations that are more prone to feel burdened, such as people with higher levels of psychopathology, should consider alternative ways of reducing such burden, such as increasing the study duration while reducing the frequency of EMA prompts during each day.

Goal two. Overall compliance, momentary predictors of compliance, dropout and related factors

The relationship between different variables and compliance at the study level, the momentary predictors of compliance, and dropout was studied. Dropout was not significantly predicted by any of the included variables (gender, age, past diagnosis, and level of psychopathology). Most dropouts (66%) occurred in the first week, suggesting that there may be certain mechanisms at play that were not investigated in this study (e.g., participants who have a low tolerance for repetitive tasks may drop out early). Compliance was quite high, with 67% of the surveys being completed. There are no guidelines about what compliance rate is acceptable in EMA studies. Some studies' compliance rates are as high as 94% (Stone et al., 2003). Note that study characteristics, such as survey frequency, can influence compliance rates (Eisele et al., 2022), but they also determine the type of phenomena that can be examined. Phenomena that unfold more slowly, require a lower frequency of assessment, and the opposite is true for faster unfolding phenomena (Wichers et al., 2021). Researchers who wish to use a protocol with a higher assessment frequency must think about the phenomena of interest, and if such a high frequency is required for the phenomena of interest.

Personal characteristics such as gender, diagnosis in the past, or level of psychopathology were not significantly associated with dropout or compliance, neither at the study level, nor at the momentary level. Females were not significantly more compliant than males, which does not align with a number of studies that observed higher compliance rates in females (Rintala et al., 2019; Vachon et al., 2019; Wrzus & Neubauer, 2023). Note that our sample size was relatively low compared to these previous studies and our sample was predominantly female. Some authors hypothesize that the inconsistent findings regarding gender and compliance might be due to complex interactions between gender and design variables such as assessment schedule, and incentives (Wrzus & Neubauer, 2023).

Concerning diagnosis and level of psychopathology, do not align with previous research that found different levels of compliance for participants with psychosis or depression in comparison to healthy participants (Rintala et al., 2019, 2020; Vachon et al., 2019). However, the present study did not include diagnosed participants, only information on lifetime diagnosis and BSI global scores was available. This aligns with the results of a meta-analysis of EMA studies, which found that participants with any clinical diagnosis did not have significantly different levels of compliance than healthy participants.

Time variables like study day and weekend did have a significant effect on compliance. Specifically, later study days had lower compliance at the study and momentary level, and Mondays and Sundays had lower compliance at the study level. Research has consistently found that later study days have lower compliance rates (Rintala et al., 2019, 2020), regardless of study duration (Vachon et al., 2019; Wrzus & Neubauer, 2023). Moreover, earlier research found Sundays to be the second-least compliant day (Rintala et al., 2019). Furthermore, the univariate model at the momentary level revealed that surveys triggered on weekends were more likely to be missed. This is not in line with a study in which weekend days were positively associated with compliance (Rintala et al., 2020). These incongruent findings might be due to the nature of the participants who were included in these studies. For example, people of different ages may spend their weekends differently, affecting compliance. For example, the average age in Rintala et al's (2020) study was 32 years old, which is ten years older than the age of our study's sample.

Survey type also had an effect on compliance at both the study and momentary level. First, shorter surveys were less likely to be missed, which is in line with earlier research (Eisele et al., 2022). Second, surveys with higher rewards were more likely to be answered, except for the morning survey, possibly because it coincided with the first momentary survey, making it the longest survey. A recent meta-analysis also showed that higher rewards increase compliance (Vachon et al., 2019). Therefore, monetary resources can be used to increase response rates for populations or moments with reduced compliance.

Finally, regarding momentary predictors of compliance, in the univariate model, positive affect at the previous time point was significantly and positively associated with the likelihood of missing a survey, which contradicts a previous study in which the opposite was observed (Rintala et al., 2020). Missing a survey at the previous time point was positively associated with the likelihood of missing a survey in the univariate model as well, which is in line with previous research (Rintala et al., 2020). Unlike in the previous study (Rintala et al., 2020), our participants received reminders to answer a survey before it expired and if a survey was missed. These reminders may have tackled the detrimental effects that missing a survey may have on compliance at the momentary level and may have caused effects not showing up anymore in the multivariate models.

Goal three. Within- and between-individual variability

The EMA items' variability was studied by means of between- and within-individuals variance and the Intra Class Correlation (ICC) in the case of quantitative items, and by means of Shannon's entropy in the case of qualitative items. Overall, our EMA protocol successfully captured experiences that change over time within individuals. All EMA items showed a degree of variability, although there were differences in the extent and type of variability between the items. Some items had very low variability, such as "use of laxatives", "purging", and "self-harm". Differences in item variability may show that items operate at different timescales (e.g., items with low variability may be operating at a slower pace). Therefore, if an item with low variability captures a relevant variable, it may still be interesting to include such an item in intensive longitudinal studies- but at a lower frequency- to see how it relates to other variables despite its low variability.

Network theory (Borsboom, 2017) is silent regarding the timescales at which different phenomena unfold. Importantly, VAR models, which are often used in this field of research, can only include variables that are assessed with the same frequency, limiting the usefulness of this statistical method. Recently, (Wichers et al., 2021) proposed the Momentary Affective Dynamics (MAD) network theory, differentiating between macro-level (i.e., symptoms) and micro-level (i.e., momentary affects) networks, with macro-level phenomena operating at a slower pace than micro-level phenomena. Wichers et al. (2021) differentiate between symptoms and momentary states, although some momentary states are listed as symptoms in the DSM-5. Note that the items with lowest within-individual variability in our set of EMA items were DSM-5 symptoms. Moreover, MAD network theory states that persistent interactions between micro-level phenomena can become interactions at the macro-level (i.e., repeated interactions between momentary affects become symptoms). It would be interesting to statistically model this type of multiple layer networks.

Goal four. Relationship between EMA items and standardized questionnaires of psychopathology

The relation between EMA items and baseline measures of psychopathology was studied by means of correlations to explore if EMA items capture psychopathology. The EMA items clearly captured psychopathology, but only some items were correlated with disorder-specific types of psychopathology (e.g., "Today my sexual desire/drive was..." correlated strongly with the Sexual Dysfunction Questionnaire), reflecting convergent validity. Strikingly, most EMA items were correlated with many scales of psychopathology; the main exception being the Autism Questionnaire and the Alcohol Use Disorder Identification Test, which had fewer and weaker correlations with the EMA items. This may suggest poor divergent validity of the EMA items. A different interpretation is that DSM categories are not as distinct as they are often presented, with many symptoms present in many diagnoses. A recent study investigated criteria repetition in 202 DSM diagnoses (Forbes et al., 2024). Only 62 (30.7%) of the included diagnoses did not have any symptom overlap with other diagnoses. Moreover, the symptoms that repeat do so 4.4 times on average, and a total of 1022 instances. Some disorders, such as bipolar and related disorders, are exclusively characterized by symptoms included in other diagnoses too. That means that it is impossible to capture bipolar psychopathology without items included in other disorders.

This overlap between DSM categories casts doubts on their validity, especially given the heterogeneity of symptoms among people with the same diagnosis. Such heterogeneity is evident in the vast number of criteria combinations, ranging from almost 24,000 for panic disorder to up to 270 million for comorbid cases like PTSD and MDD (Allsopp et al., 2019). Whereas using categories that are heterogeneous can be useful for clinicians to diagnose cases that do not fit neatly in homogeneous diagnoses, it may obscure relevant causal pathways. Such pathways could be cross-cutting symptoms or psychological processes, which, tap multiple disorders (Allsopp et al., 2019; Forbes et al., 2024).

The EMA items also correlated with the baseline transdiagnostic measures, such as fear of negative evaluation (BFNES), dichotomous thinking (DTI), self-control (SCQ), and personality (TIPI), underlining the transdiagnostic nature of the current set of EMA items, and showing the clinical validity of the included transdiagnostic measurement scales. In line with what was observed for the disorder-specific standard questionnaires, it also suggests that these transdiagnostic measures may not be specific enough to distinguish between individuals' psychological problems. Overall, the usefulness of general (DSM-5) categories or dimensions might be limited, suggesting that a more fruitful way forward lies in ideographic- and transdiagnostic approaches. More specifically, future research may need to focus more on interactions of symptoms at the individual level, and exploring specific constellations of such networks, rather than relying on common disorder categories.

Constraints on Generality

The findings presented in this study may have some constraints regarding generalizability (Simons et al., 2017). First, the generalizability of our findings is constrained to university students. Second, although our sample displayed some level of psychopathology, these findings are not generalizable to clinical samples. Finally, although our sample represented a range of nationalities, the majority were European. Therefore, generalizations to non-European populations should be made with caution.

Conclusion

The perceived burden, overall compliance, momentary predictors thereof, and dropout levels indicated that our EMA protocol is a good method to collect time-series data for estimating intraindividual networks, as well as for other analysis methods. However, this protocol still needs to be improved and adapted to different populations (e.g., clinical populations who might need less workload). Moreover, the EMA items showed considerable within-subjects and between-subjects variability, though that was not the case for all items. Measurement frequency should be adapted to the expected timescale at which a phenomenon fluctuates. Future research would benefit from statistical methods that enable the modeling of variables that develop at different timescales. The EMA items' correlation patterns with multiple types of psychopathology reflect the heterogeneity of DSM categories, and suggest that a transdiagnostic approach might be a better representation of psychopathology.

Supplementary material

Supplementary Table 1.

Overview of average and variance metrics of EMA items.

Variable	Average	Between-individuals variance	Within-individuals variance	Intra Class Correlation (ICC)
Sad	1.82	0.83	0.91	0.51
Guilty	1.61	0.78	0.72	0.59
Happy	4.01	0.97	1.05	0.48
Hopeless	1.55	0.75	0.68	0.61
Anxious	2.05	1.01	0.92	0.58
Stressed	2.46	1.00	1.11	0.48
Overwhelmed	2.14	1.00	1.02	0.53
Angry	1.38	0.54	0.62	0.52
Calm	4.12	0.92	1.07	0.45
Energetic	3.48	0.92	1.11	0.43
Lonely	1.71	0.89	0.77	0.62

Paranoid	1.28	0.53	0.40	0.70
Pain	1.5	0.63	0.70	0.53
Dizzy	1.37	0.59	0.53	0.61
Nauseous	1.39	0.65	0.57	0.63
Trembling	1.30	0.55	0.45	0.66
Racing heart	1.44	0.61	0.66	0.54
Looking forward	4.15	1.02	1.18	0.46
Self-satisfaction	4.01	1.08	0.97	0.57
Satisfaction with appearance	3.79	1.26	0.90	0.67
Cravings	1.70	0.84	0.97	0.50
Nightmare distress	1.33	0.46	0.68	0.51
Satisfaction with sleep	4.22	0.80	1.09	0.39
Restedness	3.98	0.84	1.08	0.41
Enjoyment of activity	4.22	0.83	1.22	0.34
Number of people	2.16	0.65	1.66	0.17

Enjoyment of company	2.27	1.21	2.42	0.22
Self-control	4.26	1.09	1.00	0.56
Concentration	3.93	0.96	1.09	0.46
Worry	2.58	1.00	1.13	0.47
Wrongdoing	4.68	1.01	1.02	0.52
Impulsivity	1.71	0.88	0.78	0.60
Social support	5.06	1.08	0.92	0.60
Coping	4.61	0.89	1.09	0.44
Extent avoidance social interactions	3.93	1.13	0.93	0.62
Extent avoidance objects	4.02	1.59	1.21	0.66
Extent avoidance places	4.10	1.20	0.96	0.63
Extent avoidance thoughts	3.99	1.04	0.86	0.63
Extent avoidance daily activities	4.12	1.10	0.94	0.60
Extent avoidance scary places	4.18	1.50	1.31	0.60

Extent avoidance activities	4.30	1.22	1.12	0.60
Extent avoidance pain	4.45	1.52	1.00	0.70
Extent avoidance memories	4.08	1.24	0.93	0.66
Extent avoidance intimacy	3.92	1.56	0.92	0.74
Self-harm	1.11	0.38	0.17	0.84
Watching porn	1.34	0.51	0.56	0.60
Body checking	2.53	1.30	1.03	0.63
Obsessions	2.11	1.16	0.95	0.62
Compulsions	1.90	1.05	0.84	0.63
Checking information	1.36	0.63	0.60	0.62
Social conflict	1.52	0.60	0.79	0.49
Purging	1.09	0.42	0.13	0.91
Use of laxatives	1.06	0.30	0.09	0.93
Day appraisal	4.75	0.86	1.33	0.32

Sex drive	5.31	1.06	1.19	0.47
Weekly sex	3.29	1.54	0.99	0.71
Sex satisfaction	3.79	1.57	0.77	0.79
Death wish	1.91	1.21	0.63	0.76
Life meaning	3.77	1.35	0.77	0.75

Supplementary Table 2.

Overview of average entropy metrics for EMA items.

Variable	Average entropy	Standard deviation
Food craving	0.68	0.24
Alcohol craving	0.43	0.15
Cigarettes craving	0.44	0.17
Cannabis craving	0.42	0.15
Cocaine craving	0.40	0.12
Ecstasy craving	0.40	0.12
Psychedelics craving	0.40	0.12
Other craving	0.45	0.15
E-cigarettes craving	0.42	0.13
Nightmare	0.30	0.10
Alcohol yesterday	0.31	0.11
Cigarettes yesterday	0.28	0.09
E-cigarettes yesterday	0.28	0.09
Cannabis yesterday	0.28	0.09
Cocaine yesterday	0.27	0.09
Ecstasy yesterday	0.27	0.09
Psychedelics yesterday	0.27	0.09
Other yesterday	0.27	0.09
Nothing yesterday	0.31	0.11

Activity type	0.55	0.19
Family	0.55	0.20
partner	0.58	0.25
Friends	0.71	0.23
Colleagues	0.57	0.18
Strangers	0.57	0.19
Ate nothing	0.91	0.23
Ate healthy snack	0.69	0.19
Ate unhealthy snack	0.71	0.20
Ate healthy meal	0.79	0.21
Ate unhealthy meal	0.54	0.16
Control loss eating	0.27	0.12
Smoked	0.18	0.31
Avoided interactions	0.32	0.10
Avoided objects	0.30	0.09
Avoided places	0.31	0.10
Avoided thoughts	0.32	0.10
Avoided daily activities	0.33	0.11
Avoided scary places	0.30	0.09
Avoided activities	0.31	0.10
Avoided pain	0.30	0.09
Avoided memories	0.31	0.10
Avoided intimacy	0.30	0.09

Avoided nothing	0.35	0.11
Medication	0.05	0.12
Visit doctor	0.30	0.10

Supplementary Table 3.

Descriptive values of baseline questionnaires.

Variable	M	SD	Minimum and Maximum
Somatization (BSI)	0.56	0.61	0-4
OCD (BSI)	1.14	0.85	0-4
Interpersonal (BSI)	1.14	0.89	0-4
Depression (BSI)	0.99	0.85	0-4
Anxiety (BSI)	0.83	0.72	0-4
Hostility (BSI)	0.54	0.55	0-4
Social Phobia (BSI)	0.49	0.57	0-4
Paranoia (BSI)	0.64	0.66	0-4
Psychosis (BSI)	0.74	0.73	0-4
Global (BSI)	0.80	0.57	0-4
Stress (DASS)	11.87	8.22	0-56
Anxiety (DASS)	7.13	7.22	0-56
Depression (DASS)	10.30	9.07	0-56
AQ	2.36	1.59	0-10

AUDIT	6.43	5.30	0-36
EDEQ-S	8.31	7.60	0-84
ASRS	9.23	3.86	0-24
PCL-5	19.05	14.18	0-80
SDQ	53.34	6.51	0-95
ISI	8.30	5.25	0-28
DUDIT	3.82	6.39	0-40
LPFS	2.73	0.37	1-4
BFNES	39.85	5.08	1-60
SCQ	109.81	10.78	1-180
DTI (Eating)	9.59	1.41	1-16
DTI (General)	17.71	2.11	1-28
DTI (Total)	39.15	3.21	1-64
Extraversion (TIPI)	3.95	1.66	0-12
Agreeableness (TIPI)	4.68	1.12	0-12
Conscientiousness (TIPI)	4.92	1.34	0-12

Emotional Stability (TIPI)	4.00	1.58	0-12
Openess to Experience (TIPI)	5.27	1.18	0-12

Note. BSI: Brief Symptom Inventory, DASS: Depression, Anxiety and Stress Scale, AQ: Autism Quotient, AUDIT: Alcohol Use Disorder Identification Test, EDEQ: Eating Disorder Examination Questionnaire, ASRS: Adult Attention Deficit and Hyperactivity Disorder, PCL: PTSD Check-List, SDQ: Sexual Dysfunction Questionnaire, ISI: Insomnia Severity Index, DUDIT: Drug Use Disorder Identification Test, LPFS: Levels of Personality Functioning Scale, BFNES: Brief Fear of Negative Evaluation Scale, DTI: Dichotomous Thinking Inventory, SCQ: Self-Control Questionnaire, TIPI: Ten Items Personality Inventory.

Chapter 4

Does the structure of dynamic symptom networks depend on baseline psychopathology in students?

Submitted as: Jover Martínez, A., Lemmens, L. H. J. M., Fried, E. I., Haslbeck, J.M.B., & Roefs, A. Does the structure of dynamic symptom networks depend on baseline psychopathology in students? *Behavior Research and Therapy*

Abstract:

Background: Network theory conceptualizes mental disorders as systems of dynamic interactions among symptoms and other variables, and proposes that people with psychopathology have distinct networks as compared to healthy people. However, this idea is rarely investigated, and networks are mostly estimated on cross-sectional data. Importantly, as network theory is specified on the within-person level, it is necessary to estimate networks based on intensive time-series data. This study estimated contemporaneous and temporal transdiagnostic networks on time-series data of participants with different levels of psychopathology.

Methods: 192 university students completed an Ecological Momentary Assessment (EMA) protocol. A newly developed bootstrap method was used to compare the multi-level Vector Autoregressive (mlVAR) effects between groups.

Results: Network connectivity did not differ between groups. Only a few edges differed significantly between groups, with small effect sizes.

Conclusions: These results suggest that networks of groups of people with different levels of psychopathology might not differ. Explanations and implications for these results, such as the impact of focusing on heterogeneous groups instead of homogeneous groups or individuals, the relevance of node levels, and methodological and analytical decisions, are discussed.

According to the network approach, dynamic interactions among symptoms and other relevant variables, like social context and activities (Roefs et al., 2022), constitute a mental disorder (Borsboom, 2017). These dynamic interactions may also involve symptoms that are traditionally considered as belonging to a different diagnosis, offering an alternative explanation of comorbidity. That is, the onset of a symptom shared between disorders can spread activation from one disorder to another (Cramer et al., 2010). This explanation of comorbidity renders the network approach transdiagnostic in nature.

The specific mechanisms by which activation spreads are difficult to identify because different individuals are likely to experience different symptoms, even if they share the same diagnosis (Roefs et al., 2022). In addition, different individuals may have different network structures. Despite the emphasis of the original proposition of the network approach on its dynamic intra-individual nature, most work is carried out at the between-individuals level, neglecting this dynamic nature (Robinaugh et al., 2020; Wichers et al., 2021). In line with other efforts to study the dynamic nature of networks (Roefs et al., 2022), this study examined differences in transdiagnostic temporal and contemporaneous intra-individual networks between people with different levels of psychopathology.

Network theory only makes broad suggestions about the differences between networks of people with and without psychopathology. A definition of mental health is given as “the stable state of a weakly connected network” (Borsboom, 2017, p. 9). Therefore, it can be inferred that people with low psychopathology levels will have more weakly connected networks. Moreover, the network theory posits that “individual differences [...] are due to differences in the network parameters of the corresponding symptoms” (Borsboom, 2017, p. 9). This suggests that network parameters will differ between people with different levels of psychopathology. The current study therefore tests the hypothesis that the networks of people with higher psychopathology levels contain stronger connections between nodes (i.e., higher connectivity), and we explore for which edges these differences specifically exist.

Most research in the network field so far has focused on the between-individuals level, using cross-sectional data (Wichers et al., 2021). Many of these studies focused on identifying patterns of connections between symptoms of the same disorder, different disorders, or symptoms and other relevant factors (e.g., cognitive functioning or social support; Contreras et al., 2019). Disorders such as anxiety disorders, personality disorders, and substance abuse disorders have been studied, but most attention has been paid to mood disorders, anxiety disorders, PTSD, psychosis-related conditions, and comorbid conditions (Contreras et al., 2019; Robinaugh et al., 2020; Wichers et al., 2021). These studies show how symptoms of a disorder are associated across patients, and provide insight in which symptoms(s) are most central to these disorders across people. For example, it was found that "affective instability," "identity disturbances," and "effort to avoid abandonment" were central nodes in a network of a group of patients with Borderline Peronality Disorders (BPD), and that the edge between suicidal behavior and unstable relationships was unique for patients with BPD in comparison with university students (Richetin et al., 2017).

The focus of cross-sectional network research comparing networks of groups with different levels of psychopathology is limited to date. One study found that a group of people with depressive disorder had the same network structure (i.e., pattern of connections) as a group of healthy people but connectivity was higher (Santos et al., 2017). Other studies found no significant difference in either connectivity or global structure when comparing a comorbid network of symptoms of depressive and anxiety disorder symptoms between groups with different levels of anxiety disorder (Makhubela, 2021), or when comparing a transdiagnostic network between groups with different levels of illness severity (Groen et al., 2019). Therefore, there is limited evidence to support the hypothesis that different levels of psychopathology are reflected in different network structures. However, these studies did not focus on the intra-individual level, did not consider dynamic interactions between network components, which is essential for truly testing predictions of network theory.

To study these dynamic interactions, temporal networks are estimated on intra-individual time-series data, typically gathered using Ecological Momentary Assessment (EMA; Shiffman et al., 2008). Frequently, every network's component is regressed onto itself and all other variables while controlling for the other network's components. This results in a model that informs about the temporal relations that each network component has with itself and all other components, frequently from time point t-1 to time point t. Afterwards, the residuals are used to build a contemporaneous network, which is interpreted as relations at a shorter timescale between the network's components (i.e., relations happening within the same measurement occasion), but can also represent other things such as unobserved common causes, and functional misspecification (Epskamp, Waldorp, et al., 2018).

Although the network approach focuses on intra-individual networks of symptoms from a transdiagnostic perspective, most studies on intra-individual networks focus on networks of emotions or emotions and symptoms in people with Major

Depressive Disorder (MDD; Wichers et al., 2021). There is mixed evidence regarding the differences in intra-individual networks between people with different levels of psychopathology. Some studies found that people with depressive disorder or with higher severity of symptoms of depressive disorder have more densely connected networks than healthy people (Pe et al., 2015; Wichers et al., 2020; Wigman et al., 2015). However, one study found that healthy people had a more densely connected network than people with depressive disorder (De Vos et al., 2017), and one study found that the networks of people with depressive disorder were more connected just before their symptoms improved (Van De Leemput et al., 2014). Therefore, it is not clear how differences in psychopathology are reflected in networks of emotions. Note that the only study that focused on temporal associations of symptoms found no significant differences in network density between people with remitted and persistent symptoms of depressive disorder (Groen et al., 2019).

Notably, these previous studies focused only on global network characteristics- that is, connectivity- rather than local network characteristics such as edges between specific nodes of the network. Until recently, statistical tools were unavailable to test whether these local network characteristics differed significantly between groups, and researchers could only eyeball estimated networks of different groups. Recently, a parametric permutation test (i.e., mlVAR group comparison) has been developed to statistically compare every connection in temporal and contemporaneous networks between two groups (Haslbeck et al., 2023). This study is the first to perform an mlVAR group comparison to examine differences in the network structure between people with different levels of psychopathology. Moreover, it is the first study to investigate and compare transdiagnostic networks consisting of mood, symptoms, transdiagnostic variables (e.g., concentration), and other relevant variables (e.g., social interactions). Specifically, the hypothesis that networks of people with higher level of psychopathology are more connected is tested, and differences between specific edges are explored.

Method

Participants

A total of 322 participants showed interest in the study, 288 completed the baseline questionnaire, and 262 started the EMA protocol. 238 reached the last week of the EMA protocol, and 192 completed at least 50% of the surveys. Therefore, all analyses were based on these 192 participants. Participants were students of either Maastricht, Leiden, or Amsterdam university (UvA), who were recruited via university advertisement boards, a research credit platform for students (SONA), and via social media (Instagram and Facebook). Inclusion criteria were having sufficient English proficiency and owning a smartphone. Participants received a reward for participating, which could be either a maximum of €75 in vouchers, or a combination of up to €60 in vouchers and two research credits. The value of one research credit was equivalent to one hour of work or €7.5, and the specific reward amount depended on the participants' level of compliance. The 192 participants who were included in the analyses were on average 21.92 years old (SD = 2.95), 154 (80.21%) identified as female and the rest as male; and 43 (23.40%) had received a diagnosis of a mental disorder at some point in their lives, but only three were still undergoing psychological treatment at the beginning of the study. A group with lower psychopathology levels consisted of 111 participants, and a group with higher psychopathology levels consisted of of 81 participants. The study was approved by the ethical review board of the Faculty of Psychology & Neuroscience of Maastricht University. It was preregistered on AsPredicted (https://aspredicted.org/ej6jp.pdf) under registration number 78277

Procedure

Participants could join the study between March 2nd, 2022 and May 31st, 2022. The advertisements contained a link or a QR code that directed participants to the study website, where they were informed about the study. To start the study, they were instructed to download an app from Avicenna research (https://avicennaresearch.com/), which was used for data collection. The study consisted of a screening and a monitoring phase, which are thoroughly described elsewhere (Jover Martínez, Lemmens, Fried, Guðmundsdóttir, et al., 2024), and the relevant parts are briefly described here in this paper.

The screening phase consisted of a baseline questionnaire, and a practice day on which participants familiarized themselves with the EMA protocol. When the screening phase was successfully completed, the participants began the monitoring phase. This phase consisted of 28 days of EMA, during which participants were prompted multiple times daily to respond to surveys on their smartphones. On a daily basis, participants were presented with nine surveys, and a weekly survey was administered at the end of each week. The first and last surveys of the day, and the weekly surveys provided a reward that was 50% higher than the rest of the surveys. Every approximately 7 days, participants received emails updating them on their potential rewards if they continued to maintain their current response rate. In cases of non-compliance, participants were contacted to determine the reason, and if issues were identified, efforts were made to find suitable solutions.

Measurements

Groups with different levels of psychopathology were based on scores on the BSI (de Beurs & Zitman, 2006). The BSI is a psychological self-report symptom scale consisting of 53 items (Derogatis & Melisaratos, 1983). It assesses nine dimensions of psychopathology including somatization, obsession–compulsion, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, and psychoticism. The General Severity Index (GSI) is determined by calculating the mean of all items, with elevated scores indicating increased symptom severity. Specifically, men with a GSI above 0.56, and women with a GSI above 0.71 were allocated to the high psychopathology group, and the rest of the sample was allocated to the low psychopathology group. These cutoffs were based on the minimum score of the high psychopathology category for normal populations according to de Beurs and Zitman (2006). A battery of additional questionnaires was administered at baseline, which is described elsewhere (Jover Martínez, Lemmens, Fried, Guðmundsdóttir, et al., 2024). In Table 3, mean scores on these additional questionnaires for the high and the low psychopathology group can be found.

The EMA protocol consisted of four types of surveys that assessed the whole spectrum of psychopathology. Specifically, the surveys were a morning survey (5 items), a momentary survey (up to 35 items; 8 times per day), an evening survey (up to 27 items) and a weekly survey (4 items). The morning survey coincided with the first momentary survey. Certain items were not prompted for everyone (e.g., Did you smoke since the last beep?), and other items were triggered based on the answer to previous questions (e.g., "What do you crave?" was triggered only if the answer to "At this moment, I experience cravings" was not 1). Consequently, the exact number of items could vary between participants and measurement moments. A detailed explanation on the development of this questionnaire and the specific items can be found elsewhere (Jover Martínez, Lemmens, Fried, & Roefs, 2024).

Momentary surveys were triggered with a semi-random approach within time windows lasting 1 hour, 37 minutes, and 30 seconds, following a normal distribution to increase the probability of surveys being triggered at the midpoint of the time window. The evening and weekly surveys were triggered at a specific time to enhance compliance (Eisele et al., 2022). The weekly survey expired after 12 hours, the morning and evening surveys after 45 minutes, and the remaining surveys after 20 minutes. The measurements' starting time was adapted to participants' usual waking time. Participants had the option to choose when the surveys would start being triggered based on their usual waking schedules. Participants indicated whether they typically woke up before 9 AM, between 9 and 11 AM, or after 11 AM. Depending on the choice, the first survey would be triggered between 07:30:00 AM and 09:07:30 AM, 09:07:30 AM and 10:45:00 AM, or 10:45 AM and 12:22:30 PM respectively. Table 1 includes an overview of the included items and their operationalization. All items were scored on Likert scales ranging from 1 to 7 with different labels depending on the item (Jover Martínez, Lemmens, Fried, & Roefs, 2024).

Analyses

Only the momentary surveys were used for the analyses.

Assumption checks

The mlVAR model assumes stationarity and multivariate normality. Stationary time series have unchanging means (i.e., no upward or downward trend over time) and variances (Ryan et al., 2023). In this study we checked whether means changes (i.e., the presence of mean linear trends) by regressing each variable onto a time variable with a range of 1-224, where each level represents an assessment moment for each participant separately. If time was a significant predictor for a particular variable for a particular participant at an alpha level of 0.05, that variable was considered non-stationary for that participant, and the residuals of the regression model replaced the original variable (Beltz & Gates, 2017; Ryan et al., 2023). To test for the multivariate normality of the data, the Kolmogorov–Smirnov test was used.

The mlVAR model also assumes equidistant assessment times. This assumption is violated because there is some variation in the distance between assessment points due to the pseudo-randomized assessment points, and because there is a night between the last and first assessment points of a day. To minimize the effects of such shortcoming, relations between the last assessment of a preceding day and the first assessment the day after were not estimated.

mlVAR

An mlVAR model was fitted to each of the groups using the mlVAR function of the R package mlVAR (Epskamp, Waldorp, et al., 2018). The mlVAR model is the multi-level extension of the vector autoregressive model (VAR) in which each variable at time t- 1 is regressed on itself and all other variables in the model at time t. All relations are corrected for the influence of all other variables. This model is usually depicted with a temporal network that depicts the temporal relations between the variables.

With mlVAR models, the nested structure of the data can be used to estimate idiographic deviations from the sample's coefficients (i.e., random effects). Moreover, the temporal network's residuals are used to construct an undirected contemporaneous network consisting of partial correlations that shows the relations between variables within the same time window. Individual deviations from the average relations between variables are also estimated for the contemporaneous network. Finally, the participants' means on the model's variables are used to construct a between-individual undirected partial correlation network.

The lmer estimator, which estimates the multi-level VAR model via sequential univariate multi-level estimates, was selected as it is recommended for models with more than five variables for computational reasons. Here, the random effects were not allowed to correlate. For the estimated effects of all three networks an alpha level of 0.05 was used, and a Bonferroni correction was applied to adjust for multiple testing of the null hypothesis that a relationship between two variables was present in the data. For an overview of the variables included in the networks see Table 1.

Table 1.

Overview of the variables that were included in the analyses and the EMA items on which these variables were based. Note: if multiple EMA items are mentioned, the score on the variable was computed by averaging across these items.

Variable	EMA item(s)
Positive Affect	1. Happy 2. Calm 3. Energetic
Negative Affect	1. Sad 2. Guilty 3. Hopeless 4. Anxious 5. Stressed 6. Overwhelmed 7. Angry

	8.	Lonely
	9.	Paranoid
Somative Negative Affect	1.	Pain
	2.	Dizziness
	3.	Nauseous
	4.	Trembling
Self-esteem	1.	I am satisfied with myself
	2.	I am satisfied with my physical appearance
Enjoyment of activities	1.	I look forward to completing the activities that I planned for later
	2.	How much do you enjoy what you're doing right now
Enjoyment of social activities		How much do you enjoy their [referring to a previous question: the people you are with right now] company?*
Sense of control		Since the last beep I felt like I was in control
Concentration		Since the last beep I was able to concentrate
Worry		Since the last beep I have been worrying
Impulsivity		Since the last beep I did or said something without thinking first

Note. *If the answer to the first question was 0 people, the score of Enjoyment of social activities was 0

The estimates of both the temporal and the contemporaneous networks were used to estimate network connectivity. Specifically, connectivity was computed as the absolute sum of the weighted connections (Van Borkulo et al., 2015).

Groups comparison test

The mlVAR group comparison was carried out using the mlVAR_GC function of the mnet R package (Haslbeck et al., 2023). This analysis tests the null hypothesis for each parameter that it is equal across the two groups. The low psychopathology group was coded as group 1, and the high psychopathology group as group 2. The H0 is tested with a permutation test, which repeatedly randomly shuffles participants in the two groups and re-estimates the model on the permuted data. This yields, for every parameter, a sampling distribution under the H0, which is used to compute empirical p-values using the test-statistic, which is the group difference in the respective parameter in the empirical (unpermuted) data. We run the test with 1000 permutations (Haslbeck et al., 2023). In the present study the between-group differences of each effect of the temporal and contemporaneous networks were estimated.

Results

Descriptive statistics (M, SD) and histograms of the variables based on the EMA protocol that were included in the estimated networks can be found in Table 2. All variables except impulsivity were significantly different between groups, and in the expected directions- i.e., positive things (e.g., sense of control or concentration) were higher in the low psychopathology group, and negative things (e.g., worry or impulsivity) were higher in the high psychopathology group-. Comparisons between the high and low psychopathology groups in the baseline questionnaires can be found in Table 3. Only the BSI's subscales of somatization, social phobia, and hostility were not significantly different between groups.

Assumption checks

There were 192 participants and 10 variables per participant, resulting in 1920 time series. Only 3 of 192 participants had no mean non-stationarity (1.56%). On average, 5.25 out of 10 (SD = 2.24) variables were non-stationary per participant. A total of 1009 of 1920 time series (52.55%) were non-stationary. Impulsivity was non-stationary for 69 of 192 participants (35.94%) being the most mean-stationary variable, and self-esteem was non-stationary for 119 of 192 participants (61.98%), being the least mean-stationary.

The Kolmogorov–Smirnov test was significant for all variables ($p < 0.001$), indicating that the normality assumption was violated. Because this type of data is often non-normal (Veenman et al., 2024) and no solution is currently available, no transformation was applied to the data to facilitate interpretation of the results.

Group comparison test

Connectivity in the temporal network was 5.23 for the low psychopathology group and 5.59 for the high psychopathology group. Connectivity in the contemporaneous network was 7.26 for the low psychopathology group and 7.20 for the high psychopathology group. Parametric tests could not be performed to determine whether the difference in connectivity between groups was significant because mlVAR_GC does not store the effects of each permutation. However, contrary to our hypothesis the differences were small and partly in the opposite direction.

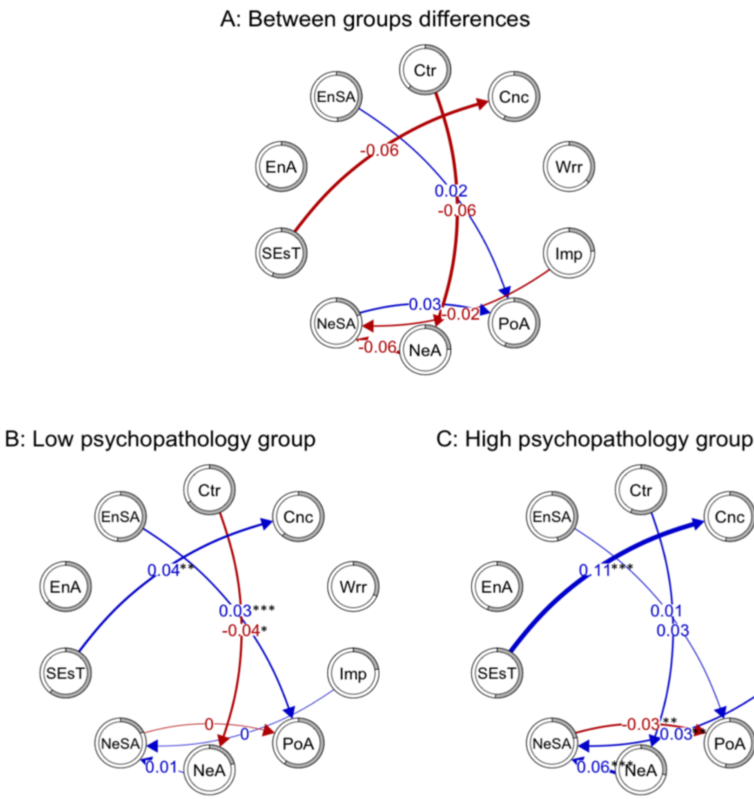
Figure 1-Panel A shows the significantly different edges between the group with low psychopathology versus the group with high psychopathology. Figure 1-Panel B and C show those specific effects in the group-specific models, and it is indicated whether such effects were significant within the group. Six significant between-group differences were found in the temporal networks, and one in the contemporaneous network. Potentially, up to 100 differences could have been found in the temporal network and up to 90 in the contemporaneous network. Therefore, contrary to our hypothesis, differences between networks of people with high and low psychopathology were rather limited, small, and some of the differences might have been false positives.

Regarding the differences in the temporal networks, two of the six significantly different relations were more positive in the low than in the high psychopathology group. That is, the positive relation between enjoyment of social activities and positive affect was stronger in the low psychopathology group than in the high psychopathology group (1). Moreover, the negative relation between negative somatic affect and positive affect was only significant in the high psychopathology group (2).

Four of the six significantly different relations were more positive in the high than in the low psychopathology group. That is, the positive relation between negative affect and negative somatic affect was only significant in the high psychopathology group (3); the positive relation between self-esteem and concentration was stronger in the high than in the low psychopathology group (4); the positive relation between impulsivity and negative somatic affect was only significant in the high psychopathology group (5), and the negative relation between sense of control and negative affect was only significant in the low psychopathology group (6). The only significantly different relation in the contemporaneous networks was between enjoyment of social activities and negative affect. This relation was negative in both groups and stronger in the high psychopathology group. Supplementary figures 1 and 2 contain the plots and coefficients of the mlVAR models of the low and high psychopathology groups.

Figure 1.

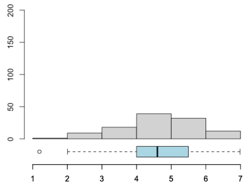
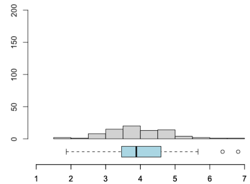
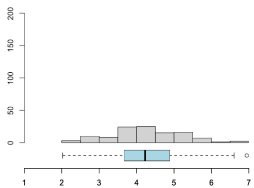
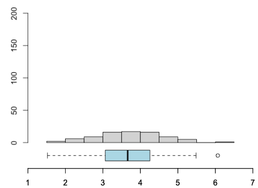
Visual representation of the results of the mlVAR group comparison test for temporal effects.

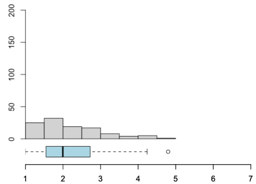
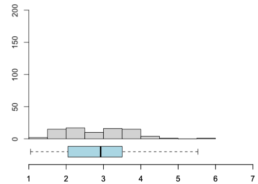
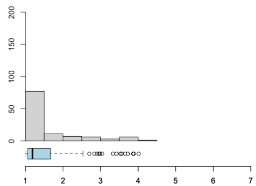
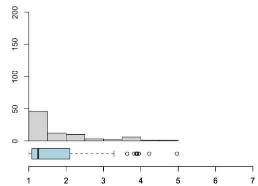
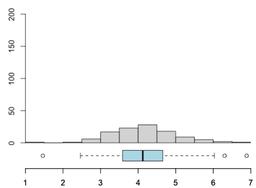
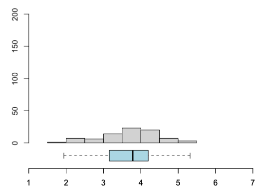


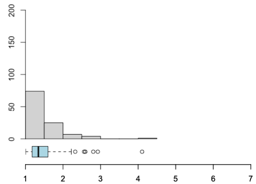
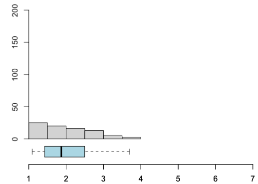
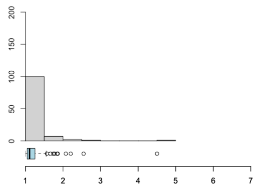
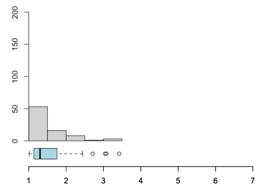
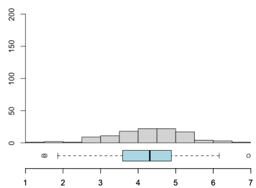
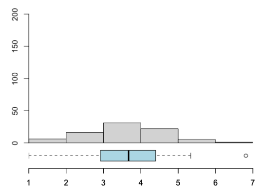
Note. Panel A: Visual representation of the significant differences between groups (i.e., low psychopathology- high psychopathology group). Panel B: Visual representation of the values of the significant edges within the low psychopathology group. Panel C: Visual representation of the values of the significant edges within the high psychopathology group. Blue lines represent positive relations and red lines negative ones. Blue lines in panel A represent a significant difference between groups, with the effect being higher in the low psychopathology group. Red lines in panel A represent a significant difference between groups, with the effect being higher in the high psychopathology group. The thicker the line is, the bigger the difference is. In panels B and C blue lines represent positive relations and red lines negative relations, and thicker lines represent stronger effects. Ctr = Sense of control, Cnc = Concentration, Wrr = Worry, Imp = Impulsivity, PoA = Positive Affect, NeA = Negative Affect, NeSA = Negative somatic affect, SEsT = Self-esteem, EnA = Enjoyment of Activities, EnSA = Enjoyment of social activities, *** = p < 0.001, ** = p < 0.01, * = p < 0.05. The gray filling in the circle around the nodes represents the group's mean score for that node.

Table 2.

Descriptives of the variables included in the estimated networks.

Variable	Low psychopathology (n = 111)		High psychopathology (n = 81)		t (df), p-value
	M (SD)	Histogram	M (SD)	Histogram	
Sense of control	4.64 (1.13)		3.97 (0.88)		4.44 (190), 0.001
Concentration	4.25 (0.93)		3.69 (0.88)		4.23 (190), 0.001

Worry	2.19 (0.84)		2.85 (0.90)		5.16 (190), 0.001
Impulsivity	1.57 (0.80)		1.75 (0.94)		1.39 (190), 0.17
Positive Affect	4.15 (0.88)		3.70 (0.73)		3.72 (190), 0.001

Negative Affect	1.47 (0.47)		1.98 (0.68)		6.18 (190), 0.001
Negative somatic affect	1.23 (0.41)		1.50 (0.51)		4.07 (190), 0.001
Self-esteem	4.24 (1.00)		3.58 (1.06)		4.40 (190), 0.001

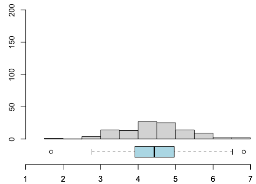
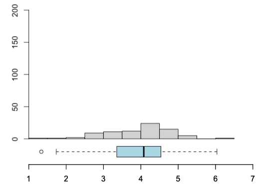
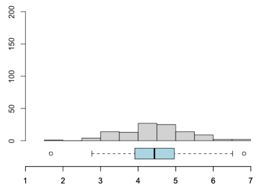
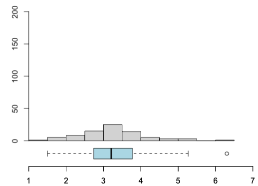
Enjoyment of activities	4.43 (0.88)		3.94 (0.86)		3.87 (190), 0.001
Enjoyment of social activities	3.64 (0.85)		3.24 (0.91)		3.12 (190), 0.002

Table 3.

Descriptives of baseline questionnaires.

Variable	Range	Low psychopathology		High psychopathology		t (df), p-value
		M	SD	M	SD	
Somatization (BSI)	0-4	0.25	0.36	0.87	0.63	1.76 (364.64), 0.08
OCD (BSI)	0-4	0.80	0.65	1.86	0.76	11.50 (292.92), 0.01
Interpersonal (BSI)	0-4	0.62	0.61	1.67	0.82	8.86 (291.08), 0.01
Depression (BSI)	0-4	0.44	0.56	1.61	0.76	7.20 (293.36), 0.01
Anxiety (BSI)	0-4	0.40	0.43	1.32	0.70	5.92 (327.36), 0.01
Hostility (BSI)	0-4	0.27	0.34	0.75	0.53	1.14 (376.73), 0.25
Social Phobia (BSI)	0-4	0.21	0.28	0.90	0.67	1.49 (360.89), 0.14

Paranoia (BSI)	0-4	0.33	0.46	0.98	0.69	3.10 (347.06), 0.01
Psychosis (BSI)	0-4	0.31	0.46	1.22	0.75	4.31 (321.34), 0.01
Global (BSI)	0-4	0.39	0.37	1.23	0.45	-
Stress (DASS)	0-56	6.92	5.56	16.80	7.26	18.37 (187.38), 0.01
Anxiety (DASS)	0-56	2.98	4.04	11.7	6.72	12.56 (178.87), 0.01
Depression (DASS)	0-56	4.57	5.83	16.9	8.90	13.52 (185.97), 0.01
Autism (AQ)	0-10	2.05	1.44	2.77	1.69	15.94 (220.97), 0.01
Alcohol use (AUDIT)	0-36	5.68	4.39	6.88	5.88	15.39 (189.4), 0.01
Eating Disorders (EDEQ-S)	0-84	5.40	5.85	10.30	8.14	13.22 (187.65), 0.01
ADHD (ASRS)	0-24	7.53	3.45	10.9	3.44	30.41 (192.08), 0.01
PTSD (PCL-5)	0-80	11.2	9.08	27.5	13.10	17.88 (186.48), 0.01

Sexual problems (SDQ)	0-95	52.4	6.20	54.7	6.82	110 (188.06), 0.01
Sleeping difficulties (ISI)	0-28	6.29	4.37	10.40	5.16	20.29 (189.35), 0.01
Drug use (DUDIT)	0-40	2.29	3.90	4.40	7.23	6.69 (188.77), 0.01
Personality pathology (LPFS)	1-4	2.57	0.32	2.92	0.32	51.49 (352), 0.01
Fear of Negative Evaluation (BFNES)	1-60	38.50	3.72	42.00	6.04	104.51 (189.35), 0.01
Self-Control (SCQ)	1-180	108	10.5	112	10.7	138.49 (186.77), 0.01
Eating Dichotomous Thinking (DTI)	1-16	11.4	1.33	11.7	1.40	104.70 (232.99), 0.01
General Dichotomous Thinking (DTI)	1-28	21.7	2.20	21.5	2.47	122.8 (202.59), 0.01
Total Dichotomous thinking (DTI)	1-64	47.4	3.06	48.4	3.39	198.03 (194.47), 0.01
Extraversion (TIPI)	0-12	4.26	1.68	3.48	1.59	27.33 (217.27), 0.01
Agreeableness (TIPI)	0-12	4.91	1.15	4.42	1.19	45.40 (247), 0.01

Conscientiousness (TIPI)	0-12	5.28	1.16	4.83	1.25	48.51 (244.29), 0.01
Emotional Stability (TIPI)	0-12	4.67	1.42	3.19	1.32	30.19 (222.25), 0.01
Openness to Experience (TIPI)	0-12	5.22	1.12	5.21	1.29	50.88 (246.93), 0.01

Note. BSI: Brief Symptom Inventory, DASS: Depression, Anxiety and Stress Scale, AQ: Autism Quotient, AUDIT: Alcohol Use Disorder Identification Test, EDEQ: Eating Disorder Examination Questionnaire, ASRS: Adult Attention Deficit and Hyperactivity Disorder, PCL: PTSD Check-List, SDQ: Sexual Dysfunction Questionnaire, ISI: Insomnia Severity Index, DUDIT: Drug Use Disorder Identification Test, LPFS: Levels of Personality Functioning Scale, BFNES: Brief Fear of Negative Evaluation Scale, DTI: Dichotomous Thinking Inventory, SCQ: Self-Control Questionnaire, TIPI: Ten Items Personality Inventory.

Discussion

The current study investigated whether groups with different levels of psychopathology have different network structures. It was hypothesized that the network of the group high in psychopathology would be more connected. However, overall network connectivity was not stronger in the high than in the low psychopathology group. Moreover, few significant differences of specific edge weights were found between groups, and resulting differences were small. Interestingly, despite these few and small differences in edge weights between the two groups, node means were largely significantly different between groups and in the expected direction.

Several differences in edge-strength were observed between the two groups, which will be discussed in turn. First, the positive relation between enjoyment of social activities and positive affect was stronger in the low psychopathology group than in the high psychopathology group. This finding is in line with studies that found an association between social activities and positive affect in community and student samples (Berry & Hansen, 1996; Watson et al., 1992). Relatedly, like in the present study, such studies did not find an association between enjoyment of social activities and negative affect. In conclusion, not only do people with higher psychopathology enjoy social activities less (i.e., lower average score on node), social activities also benefit them less, as the increase in positive affect on the next time point is weaker.

Second, the negative relation between negative somatic affect and positive affect was only significant in the high psychopathology group. Thus, the experience of negative somatic affect led to a reduction of positive affect on the next time point in the high psychopathology group only. The negative association between pain and positive affect is well-replicated by multiple studies, including a meta-analysis (Ong et al., 2020). However, pain literature theorizes that the effect is in the opposite direction that we found (i.e., the effects of positive affect on pain). For example, some researchers attribute positive affect a "buffering" role that prevents pain (Thong et al., 2016), or an attenuating effect that reduces pain (Hanssen et al., 2017). Negative somatic affect was composed of items other than pain, but the relation between other somatic symptoms and positive affect is studied in the same direction (the effects of positive affect on somatic symptoms; Schenk et al., 2017). Therefore, future research should investigate if somatic symptoms influence positive affect, and if the relation differs between levels of psychopathology as we found in the present study.

Third, the positive relation between negative affect and negative somatic affect was only significant in the high psychopathology group. This finding aligns with the well-established relation between negative affect and pain. Negative affect is known to increase pain-sensitization through different mechanisms such as increased attention (Janssen, 2002). Fourth, the positive relation between self-esteem and concentration was stronger in the high than in the low psychopathology group. This suggests that the ability to concentrate depended more strongly on self-esteem in the high psychopathology group. Prior research has shown that self-esteem is a protective factor for concentration (Boulton & Macaulay, 2023). The current research suggests that this might be especially true for people scoring higher on psychopathology, possibly due to the average lower level of self-esteem in this group.

Fifth, the positive relation between impulsivity and negative somatic affect was only significant in the high psychopathology group. It is hard to interpret this finding, as it cannot be related to prior research or theory. A final between-group difference in the temporal networks was that the negative relation between sense of control and negative affect was only significant in the low psychopathology group. Specifically, when the low psychopathology group feels in control, they experience less negative affect at the next time point. Moreover, given the difference of sense of control at the group-level, not only does the high psychopathology group experience being in control less often, it also does not lead to a reduction of negative affect in them either. The link between sense of control and positive affect has been established in multiple studies. An increase of sense of control in a 2-year follow up was associated with positive affect (Hong et al., 2021). Moreover, sense of control has been shown to mediate the effect between different variables and positive affect, such as dispositional mindfulness and perceived discrimination (Imel & Dautovich, 2016; Jang et al., 2008). Note that impairment of control is associated with depression, stress, and anxiety-related disorders (Abramson et al., 1989; Chorpita et al., 1998; Shapiro et al., 1996).

For the contemporaneous networks, it was found that enjoyment of social activities coincided with a reduction of negative affect, and this relationship was more pronounced for the high psychopathology group. This contrasts with studies that find no relationship between social activities and negative affect (Berry & Hansen, 1996; Watson et al., 1992). However, these studies are either laboratory experiments or examine the frequency of social interaction without considering whether participants enjoyed such activities. The present study was conducted in real life, and our social activity variable focused on the enjoyment of such activities rather than the frequency. Our finding suggests that if people with higher levels of psychopathology enjoy social activities- even though on average they report less enjoyment- it does coincide with a reduction of negative affect, underlining the importance of social activities for this group.

Zooming out, it needs to be concluded that results are overall not in line with the hypothesis of a more densely connected network in people with higher levels of psychopathology. Moreover, very few temporal and contemporaneous associations between the selected nodes differed between the groups. The nodes' averages were different between groups. That is, people with higher levels of psychopathology scored higher on almost all included variables in the networks. This suggests that, although the relations between nodes are the same at across psychopathology severity, such relations might operate at a different level. For example, though worry leads to negative affect across psychopathology severity, the level of both variables is higher in the high psychopathology group.

However, our sample included university students and results might be different when including people with a clinical diagnosis of a mental disorder. Moreover, the current analyses compare effects separately, instead of the network as a whole. Recent efforts applying invariance testing to idiographic networks have made it possible to compare temporal networks of different individuals (Hoekstra et al., 2024). Unfortunately, such analyses are not available for multi-level temporal networks.

Also, the present study aimed at studying networks including variables reflecting a broad range of psychological problems (i.e., transdiagnostic networks). Studying this type of networks can be useful to map relevant processes (Roefs et al., 2022). However, zooming-in on such processes might be necessary to fully understand them. In other words, higher-level networks are useful to map relevant processes that will be better understood through lower-level networks. Therefore, lower-level networks should focus on specific processes, such as the relations between specific thoughts, motivations, coping mechanisms, and outcomes thereof. For example, two individuals may show the same behavior but such behavior might be differently motivated. That difference in motivation might be clinically relevant.

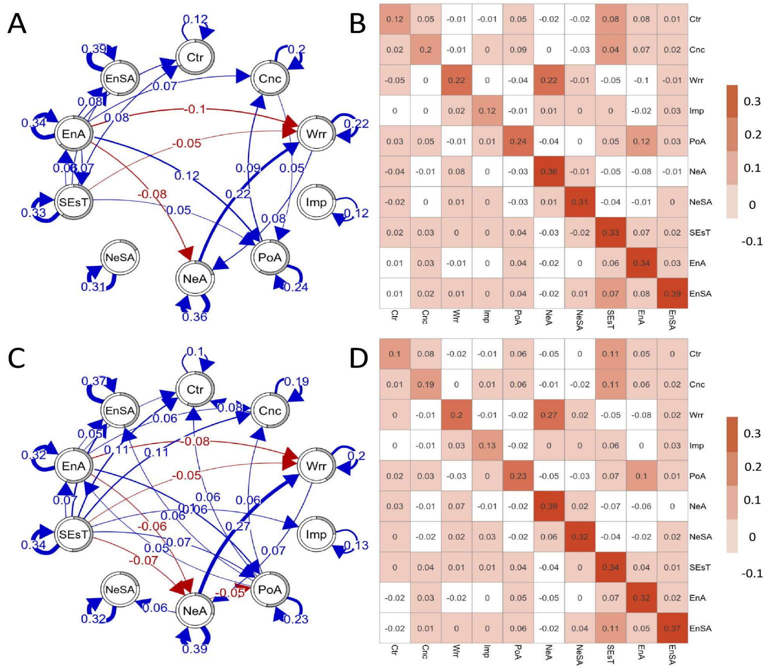
Studying lower-level networks also implies shifting the focus from a small number of groups with high within-group heterogeneity to a larger number of groups with high within-group homogeneity. For the sake of clinical utility, such homogeneous groups should reflect specific causal processes (Roefs et al., 2022), rather than the co-occurrence of psychological phenomena as done by the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM–5; American Psychiatric Association, 2013). Unfortunately, what processes should be studied, and what variables reflect those processes well, are unknown. Cluster research on higher-level networks might help identifying groups driven by different processes and the variables implied in such processes. As a consequence of those different processes, network comparison analyses on such clusters might reveal more differences.

Conclusion

The present study examined if groups with different levels of psychopathology exhibit different network structures. It was hypothesized that the network of the group with high psychopathology would show greater connectivity. However, the connectivity or network structure did not differ between groups with different levels of psychopathology. However, average scores on the variables included in the networks and on the baseline questionnaires did differ between groups in the expected direction. This suggests that the nodes of groups with different levels of psychopathology are interrelated in the same way, but the system operates at a different level. However, the results might have been different in a clinical sample. Zooming-in lower-level networks might also reveal specific processes which differ more between homogeneous groups. It is therefore recommended that future research cluster higher-level networks to identify homogeneous groups. Networks of such homogeneous groups should be studied at a lower level (i.e., specific thoughts, motivations, coping mechanisms, and outcomes thereof) to reveal clinically-relevant processes that may differ between levels of psychopathology or between groups suffering from different psychopathological processes.

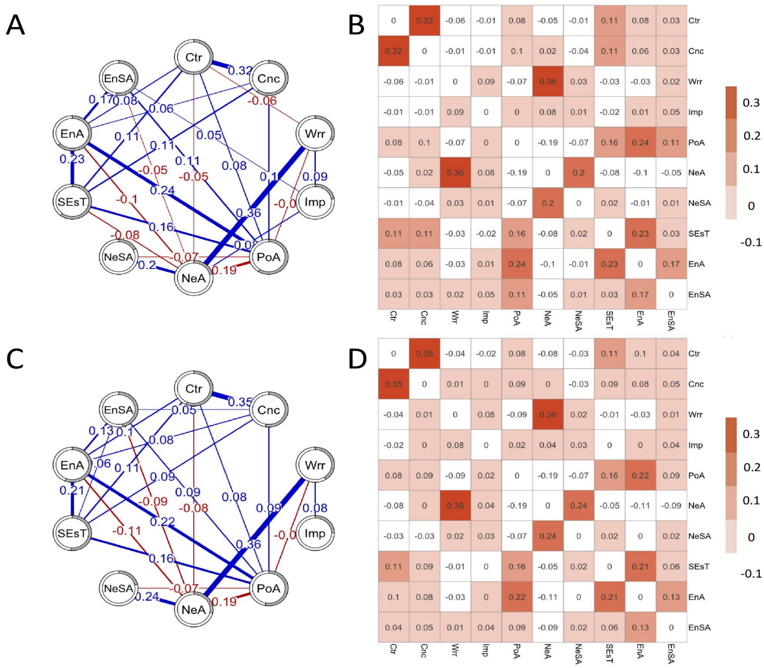
Supplementary material

Supplementary figure 1. Plots and coefficients of the temporal networks of the low and high psychopathology groups.



Note. The direction of the effects in the heatmaps go from column to row. Effects below 0.05 were not included in the network plots. Blue lines represent positive relations and red lines negative ones. The thicker the line is the stronger the relation is. The gray filling in the circle around the nodes represent that group's mean score for that node. Panels A and B are the network plot and heatmap of the low psychopathology group, and C and D of the high psychopathology group. Ctr = Sense of control, Cnc = Concentration, Wrr = Worry, Imp = Impulsivity, PoA = Positive Affect, NeA = Negative Affect, NeSA = Negative somatic affect, SEsT = Self-esteem, EnA = Enjoyment of Activities, EnSA = Enjoyment of social activities

Supplementary figure 2. Plots and coefficients of the contemporaneous networks of the low and high psychopathology groups.



Note. The direction of the effects in the heatmaps go from column to row. Effects below 0.05 were not included in the network plots. Blue lines represent positive relations and red lines negative ones. The thicker the line is the stronger the relation is. The gray filling in the circle around the nodes represent that group's mean score for that node. Panels A and B are the network plot and heatmap of the low psychopathology group, and C and D of the high psychopathology group. Ctr = Sense of control, Cnc = Concentration, Wrr = Worry, Imp = Impulsivity, PoA = Positive Affect, NeA = Negative Affect, NeSA = Negative somatic affect, SEsT = Self-esteem, EnA = Enjoyment of Activities, EnSA = Enjoyment of social activities.

Chapter 5

Robustness, generalizability, and heterogeneity of dynamic networks of psychopathology.

Submitted as: Jover Martínez, A., Lemmens, L. H. J. M., Fried, E. I., Waldorp, L. J., & Roefs, A. Robustness, generalizability, and heterogeneity of dynamic networks of psychopathology. *Multivariate Behavioral Research*

Abstract:

The network perspective of psychopathology proposes that mental disorders arise from dynamic interactions between psychopathology-relevant variables. This study explored the robustness, generalizability, and heterogeneity of dynamic networks of psychopathology using Ecological Momentary Assessment data of 173 participants. Robustness- i.e., how precisely model parameters are estimated- of nomothetic networks was assessed via case-dropping bootstrapping. Translatability (i.e., how much group-derived estimates reflect individual processes) was evaluated by comparing freely estimated idiographic networks to idiographic networks where significant effects from the nomothetic network were constrained. Heterogeneity was analyzed using the Individual Network Invariance Test per pair of individuals. Results suggest that robustness was acceptable overall. Translatability from nomothetic to idiographic networks was limited, and inter-individual heterogeneity was large. The limited generalizability and large heterogeneity shows the urgency of finding homogeneous groups. Recommendations to find such groups combining data-driven and theory-driven approaches with a focus on single-case research are discussed.

The network perspective to psychopathology offers an alternative view to the medical model of mental disorders (Borsboom, 2017). Rather than attributing the symptoms of mental disorders to an underlying cause in the brain, as proposed by the medical model (Bruce, 2009; Deacon, 2013), this approach suggests that a mental disorder arises from dynamic interactions between symptoms (Borsboom, 2017). Such dynamic interactions occur between symptoms within and across diagnostic categories (Cramer et al., 2010) rendering the network approach transdiagnostic in nature. Besides symptoms, other variables have been proposed to be included in psychopathology networks, such as context, behaviors, or social interactions (Jones et al., 2017; Roefs et al., 2022). The focus of the network approach on dynamics over time has brought about several challenges. The goal of this study is to investigate three of such challenges. First, the robustness of nomothetic dynamic networks was examined. Second, as the shift on temporal dynamics allows studying idiographic processes, the generalizability from nomothetic to idiographic temporal networks was studied. Finally, the heterogeneity of idiographic dynamic networks was investigated.

Goal one: robustness of nomothetic dynamic networks

Robustness, is defined as "the stability of statistical inference under variations of the accepted distribution models" (Shevlyakov & Vilchevski, 2002) (Shevlyakov & Vilchevski, 2002, p.7). In other words, robustness reflects whether the model estimation remains the same when data are obtained from different distributions, usually reflected in small variations of the data (e.g., bootstrapped samples, case-dropping). The robustness of certain types of network models has not been investigated yet. Network model estimates are susceptible to low power and violations of normality, both of which are common in psychological research (Blanchard et al., 2022; Epskamp, Borsboom, et al., 2018). Therefore, studying the robustness of networks is crucial to ensure the reliability of results (Blanchard et al., 2022; Epskamp, Borsboom, et al., 2018).

The robustness of cross-sectional networks (i.e., undirected network models estimated on between-individuals data) has been addressed frequently using case-dropping bootstrapping methods (Blanchard et al., 2022; Epskamp, Borsboom, et al., 2018). Specifically, new datasets are created by re-sampling cases with replacement, and the same network model is fit on each dataset. The parameters obtained from the fitted networks form a sampling distribution, and a bootstrapped confidence interval can be estimated (Epskamp, Borsboom, et al., 2018). Cross-sectional networks can be estimated robustly, but only with enough power and bootstrap permutations (Blanchard et al., 2022; Epskamp, Borsboom, et al., 2018). However, cross-sectional networks only inform about interactions between variables at one time point at the between-subjects level (Epskamp, Borsboom, et al., 2018).

Dynamic networks (i.e., network models estimated on temporal data) inform about the temporal relations between variables, which is crucial given the dynamic nature of network theory of psychopathology (Borsboom, 2017) and most psychological variables (Blanchard et al., 2022; Bringmann et al., 2022). Dynamic networks can entail a temporal network- reflecting temporal relations between measurement points- and a contemporaneous network reflecting relations within measurement points (Epskamp, Waldorp, et al., 2018). Different ways of studying robustness of dynamic networks have been suggested, such as case-dropping bootstrapping methods, or dropping blocks of data within-individuals, instead of full individual's data to account for temporal dependencies (Epskamp, Waldorp, et al., 2018). A study that estimated dynamic idiographic networks, pooled the idiographic networks together, and used a case-dropping bootstrapping method to examine the robustness of the pooled parameters. It was found that the contemporaneous networks were robust but the temporal networks were not (Lazarus et al., 2021).

Otherwise, the robustness of dynamic networks has been neglected. This could be because researchers prefer to estimate nomothetic dynamic networks instead of pooling the idiographic networks of different participants unless the sample is homogeneous (De Vos et al., 2017). However, the robustness of multi-level dynamic networks has not been studied to our knowledge because bootstrapping methods for such models are very computationally demanding (Bringmann et al., 2013). In the present study, the robustness of multi-level Vector Autoregressive model (Epskamp, Waldorp, et al., 2018) of transdiagnostic psychopathology was studied.

Goal two: generalizability from nomothetic to idiographic networks

The generalizability of nomothetic models to idiographic models- that is, whether group-derived estimates reflect idiographic processes (Fisher et al., 2018)- has been overlooked (Hamaker, 2012). Most research on the network approach is mostly carried out at the nomothetic level, ignoring if the studied processes apply to specific individuals and potentially compromising clinical utility.

To investigate within-individual relationships among variables in a network researchers typically estimate temporal networks. However, researchers investigating within-individual relationships use methods that might not consider the individual enough. For example, studies estimating one idiographic network per participant frequently pool such networks together. Pooled results do not represent the different individuals in the group sufficiently unless the group is homogeneous (i.e., the individuals are similar), but that is rarely the case (De Vos et al., 2017; Molenaar & Campbell, 2009). Another approach taking within-individual variation into account are multilevel models such as mlVAR models. However, multi-level models like mlVAR rely heavily on the between-subjects parameters (i.e., shrinkage; Epskamp, Waldorp, et al., 2018) (Epskamp, Waldorp, et al., 2018). Thus, despite these attempts to approach the individual level, mlVAR relies heavily on group-based parameters.

Assuming that nomothetic results apply to all individuals poses a threat to social and medical sciences as there is evidence showing that this is likely not the case (Fisher et al., 2018; Hamaker, 2012). Given the clinical utility of knowledge of idiographic processes, researchers should study the generalizability of nomothetic results to the idiographic level (Fisher et al., 2018). In the present study, a freely estimated idiographic network model (hereon termed unconstrained model) and a idiographic network model where the parameters that were significant in the nomothetic network model were estimated (hereon termed constrained model) for each individual. After that, the difference in the goodness of fit was estimated to examine which model has a better fit. If most individuals display a better fit in the unconstrained model, it suggests that the nomothetic network does not translate optimally.

Goal three: heterogeneity of networks of individuals

Investigating the heterogeneity of idiographic networks is crucial for understanding the generalizability from nomothetic to idiographic networks.The lack of generalizability of parameters derived from groups to individuals could be due to high heterogeneity. That is, parameters derived from a group consisting of very different individuals will not represent all individuals well. Moreover, understanding the degree of heterogeneity of networks is critical for the development of personalized interventions (Hoekstra et al., 2023).

Previous research suggests that idiographic networks are heterogeneous (Beck & Jackson, 2020; De Vos et al., 2017; Levinson et al., 2022; Piccirillo & Rodebaugh, 2022; Reeves & Fisher, 2020). However, this research relied on visual inspection of estimated networks to make inferences about the observed heterogeneity. Moreover, these studies attributed all heterogeneity to individual differences, ignoring sampling variability and limited power to properly assess inter-individual heterogeneity (Hoekstra et al., 2023). The present study investigates heterogeneity by examining differences in the network structure of each pair of individuals. To do so, we use a recently developed statistical test rather than relying on visual inspections.

Method

Participants

A group of 322 participants started the study, 288 completed the baseline questionnaire, 262 began the EMA protocol, and 238 reached the final week of the protocol. Participants who completed at least 50% of the EMA-surveys were included in the analyses (n = 192). Due to lack of variance in at least one variable of the model, 16 participants needed to be removed from the analyses. Finally, estimation and convergence problems for 3 participants required their removal, leaving a final sample of 173 individuals. The average age of participants was 21.9 years (SD = 2.8), 83.3% were female (n = 140), and 21.6% (n = 37) reported having been diagnosed with a mental disorder at some point in their lives. At the beginning of the study, only three participants were undergoing treatment for a mental disorder. The study received approval from the ethical review board of the Faculty of Psychology & Neuroscience at Maastricht University and was pre-registered on AsPredicted (https://aspredicted.org/ej6jp.pdf) with registration number 78277.

Procedure

For a complete description of the procedure of the study, see (Jover Martínez, Lemmens, Fried, Guðmundsdóttir, et al., 2024). The study consisted of a baseline questionnaire including standardized measures of psychopathology, an EMA practice day, and an EMA study that lasted 28 days during which different types of surveys were triggered with different frequencies. Specifically, there was a morning survey, and an evening survey triggered once per day, a weekly survey triggered once per week, and and a momentary survey triggered 8 times per day (one of them together with the morning survey). For the present study, only momentary surveys were used (i.e., surveys triggered 8 times per day). Therefore, participants could answer up to 224 data points. Participants were rewarded based on the number of surveys they answered. Moreover, different surveys were rewarded differently. For example, the first survey of the day, which included items about sleep, had a reward twice as high as a regular survey.

Surveys were triggered semi-randomly within time windows of 1 hour, 37 minutes, and 30 seconds. Moreover, surveys were triggered following a normal distribution (i.e., the chances of a survey triggered in the middle of the time interval were maximized) and the start of the daily triggers was adapted to participants' usual waking times. All momentary surveys contained the same items. However, depending on the answer to the baseline questionnaire, some items were not triggered. For example, "Did you smoke since the last beep?" was only triggered if the participant indicated to be a smoker in the baseline questionnaire. Similarly, some items were contingent on answers to previous questions. For example, "What do you crave?" was only triggered when answering positively to the item "At this moment, I experience cravings". All items were scored on Likert scales ranging from 1 to 7. The first moment (i.e. morning and first momentary surveys) expired after 45 minutes, and the others after 20 minutes.

Push notifications were sent when a survey was triggered, and 12 minutes before the expiration of the survey. An extra push notification for the first survey was sent 30 minutes before expiration. Every approximately 7 days, participants received emails updating them on their potential rewards if they continued to maintain their current response rate. In cases of non-compliance, participants were contacted to determine the reason, and if issues were identified, efforts were made to find suitable solutions.

Measurements

For an overview of all the items triggered in the EMA study see (Jover Martínez, Lemmens, Fried, & Roefs, 2024). In the current study, only a selection of items from the momentary surveys were used: positive affect, negative affect, somatic negative affect, self-esteem, enjoyment of activities, enjoyment of social activities, sense of control, concentration, worry, and impulsivity. Some of these variables were averages of a few items (e.g., positive affect, or negative affect). For the specific variable configuration see (Jover Martínez, Lemmens, Fried, Guðmundsdóttir, et al., 2024).

Analysis

All analyses were performed using R 4.2.2 (R Core Team, 2016) and consisted of Vector Autoregressive (VAR) models. VAR models are linear time series models in which each variable at a previous time point is regressed on itself and all other variables in the model at a later time point (Brandt & Williams, 2007). For all models in the present study, lag-1 models- i.e., model estimating effects between t- 1 and t were used-. VAR models for n = 1 (i.e., idiographic models) were estimated using the package graphicalVAR (Epskamp, Waldorp, et al., 2018). This model provides two networks, a temporal network showing the temporal effects between variables, and a contemporaneous network showing the relations between the nodes' residuals after fitting the temporal network. Such residuals are theorized to include relations that occur at a faster time scale than the relations captured in the temporal network (Hoekstra et al., 2024). Moreover, mlVAR models for n > 1 (i.e., nomothetic models) were estimated using the mlVAR package to account for the nestedness of the data. Sequential univariate multilevel estimation with orthogonal estimation of the random effects was used in mlVAR because it is recommended for networks with more than five nodes(Epskamp, Waldorp, et al., 2018). Besides temporal and contemporaneous networks, mlVAR models estimate a between-individuals network, modeling the average parameters in the sample (i.e., the fixed effects). However, the between-individuals network does not reflect dynamic relations, and was not included in this study as it ir out of scope.

Goal one: robustness of dynamic networks

The robustness of temporal and contemporaneous networks estimated with mlVAR was studied. To study robustness of mlVAR, a non-parametric bootstrapping method was used where 75% of participants were sampled with replacement in 100 permutations. In each iteration, an mlVAR model was fitted. Usually, 500 permutations lead to accurate inference in bootstrapped analyses (Davison & Hinkley, 1997). However, any cutoff in the number of permutations is arbitrary (Haslbeck et al., 2023), and 500 permutations would be too demanding for the estimation of mlVAR models (Bringmann et al., 2013).

After the bootstrapping routine was completed, a sampling distribution for every relationship between the network's nodes was created. This sampling distribution was used to estimate bootstrapped means, and bootstrapped Confidence Intervals (CI) based on the 0.025 percentile and 0.975 percentile. Moreover, the number of iterations that each effect in the networks was significant was estimated. In the temporal network, the relations are directed and include effects of each node with themselves. Therefore, n^2 relations are estimated. In this study there were 10 nodes, which results in 100 relations. In the contemporaneous and network the relations are undirected and do not include effects of the nodes with themselves. Therefore, only (n x (n- 1))/2 relations are estimated. In this study there were 10 nodes, which results in 45 relations for the contemporaneous network.

Goal two: generalizability from nomothetic to idiographic networks

First, an mlVAR model was estimated for the whole sample to estimate the nomothetic model. Second, a graphicalVAR model was estimated per individual (i.e., an idiographic model) without any constraints (i.e., unconstrained model), and a gamma parameter of 0.5 (Foygel & Drton, 2010). Third, a constrained graphicalVAR model was estimated per individual where only the effects that were significant in the nomothetic model were estimated (i.e., constrained model). Finally the Estimated Bayesian Information Criterion (EBIC) of the constrained model was subtracted from the unconstrained model to determine which model had better fit ($EBIC_{unconstrained}$- $EBIC_{constrained}$). Lower EBIC indicates a better fit, which means that, after the subtraction, negative values indicated a better fit for the unconstrained model, and positive values indicated a better fit for the constrained model.

In the constrained model, the effects from nomothetic network were always included in each idiographic model, to test how well the nomothetic network fits each individual's data. This means that effects were included that might not have been present if the model had been estimated without constrains. In other words, false positives might have been forced. Therefore, the percentage of effects close to 0 was estimated for the constrained model as an indicator of potential false positives. Specifically, the percentage of effects between-0.1 and 0.1, and between-0.05 and 0.05 were estimated. That percentage was also estimated in the unconstrained model to examine how different the percentage between models was.

Goal three: heterogeneity of networks of individuals

The heterogeneity of idiographic networks was studied by means of the recently developed Individual Network Invariance Test (INIT; Hoekstra et al., 2024) (Hoekstra et al., 2024). The INIT assesses the similarity of two network structures. In the INIT two models were compared: a heterogeneous model and a homogeneous model. The heterogeneous model allowed the network relations to vary between networks, and the homogeneous model kept the network relations constant across networks. Afterwards, the homogeneous model's Akaike Information Criteria (AIC) was subtracted from the heterogeneous model's AIC ($AIC_{heterogeneous}$- $AIC_{homogeneous}$). Lower AIC values indicate better fit, which means that, after the subtraction, negative values indicated a better fit for the heterogeneous model, indicating that individuals were different, and positive values indicated a better fit for the homogeneous model, indicating that individuals were not different. In the present paper, all relations in the models were estimated (i.e., the models were saturated), and a comparison for every pair of individuals was performed. Given that the sample consisted of 173 participants, (n x (n- 1))/2 comparisons were performed, leading to a total of 14,878 comparisons.

Results

Goal one: robustness of dynamic networks

Figure 1 provides a visual representation of the robustness results, which overall suggest that the mlVAR estimates were robust. The group means and bootstrapped means were very similar for all networks, meaning that estimates were robust to sampling variation. The confidence intervals were narrow for the temporal and contemporaneous networks (panels A and B of Figure 1 respectively). Regarding the significance of the effects, 17 relations (17%) for the temporal network, and 7 effects for the contemporaneous network (15.6%) were not significant consistently (i.e., such effects were significant only between 10% and 90% of the iterations). Evidence for 24 effects in the temporal network (24%), and 6 in the contemporaneous network (13.3%) was not consistently absent (i.e., the confidence intervals contained 0).

Goal two: generalizability from nomothetic to idiographic networks

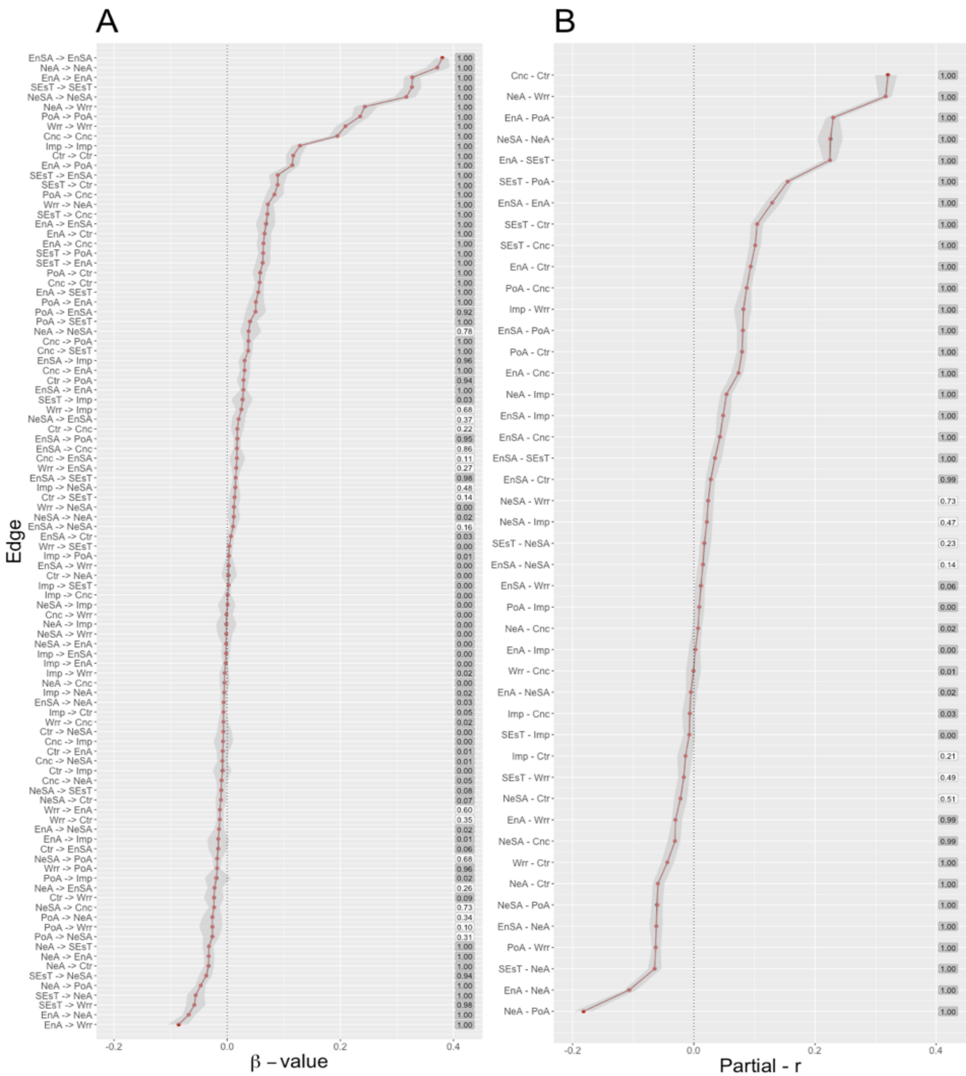
Figure 2 shows the difference between the constrained and unconstrained models on the AIC. The constrained model had a better fit for 126 (72.83%) participants, and the unconstrained model had a better fit for 47 (27.17%) participants. Together, this suggests that the nomothetic model generalized well to most idiographic models. However, 51.56% of the constrained model's parameters were between-0.1 and 0.1, whereas only 35.17% of the unconstrained model's parameters were within that range. Moreover, 28.63% of the constrained model's parameters were within-0.05 and 0.05, but only 14.17% of the unconstrained model's parameters were within that range. Thisindicates that due to the forcing of parameters in the constrained model's some of such parameters might have been false positives.

Goal three: heterogeneity of networks of individuals

Figure 3 represents the difference in AIC for each comparison between pairs of individuals. Overall, the figure shows that the homogeneity model (constraining network structures of two individuals to the same structure) had a better fit in most comparisons than the heterogeneity model (allowing network structures of two individuals to be different). Specifically, in 11,085 (74.51%) of the model comparisons, the homogeneous model had a better fit, and in 3,793 (24.49%) the heterogeneous model had a better fit. 330 comparisons (2.21%) had a standard deviation above 1 or below-1 and were removed from the plot to improve legibility.

Figure 1.

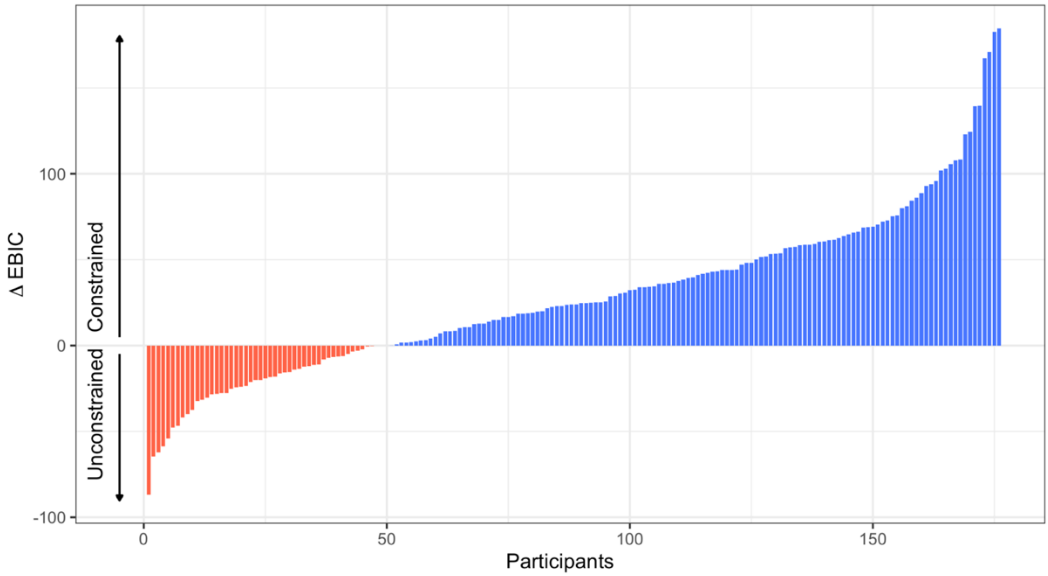
Visualization of robustness analyses.



Note. A: Robustness results for temporal networks, B: Robustness results for contemporaneous networks. Red dots represent the values for the group model means, and black dots for the bootstrapped means. The gray shadows represent the CI, and the numbers in boxes the proportion of iterations each effect was significant. Grey boxes represent effects that were significant in 90% of iterations or more (i.e., consistently observed), or 10% of iterations or less (i.e., consistently not observed), whereas white boxes represent effects that were significant in between 11% and 89% of iterations. Ctr = Sense of control, Cnc = Concentration, Wrr = Worry, Imp = Impulsivity, PoA = Positive Affect, NeA = Negative Affect, NeSA = Negative somatic affect, SEsT = Self-esteem, EnA = Enjoyment of Activities, EnSA = Enjoyment of social activities.

Figure 2.

Distribution of EBIC differences.



Note. ΔEBIC = $EBIC_{unconstrained}$- $EBIC_{constrained}$. Red bars indicate a better fit for the unconstrained model and blue bars indicate a better fit for the constrained model. Each column represents a participant.

Discussion

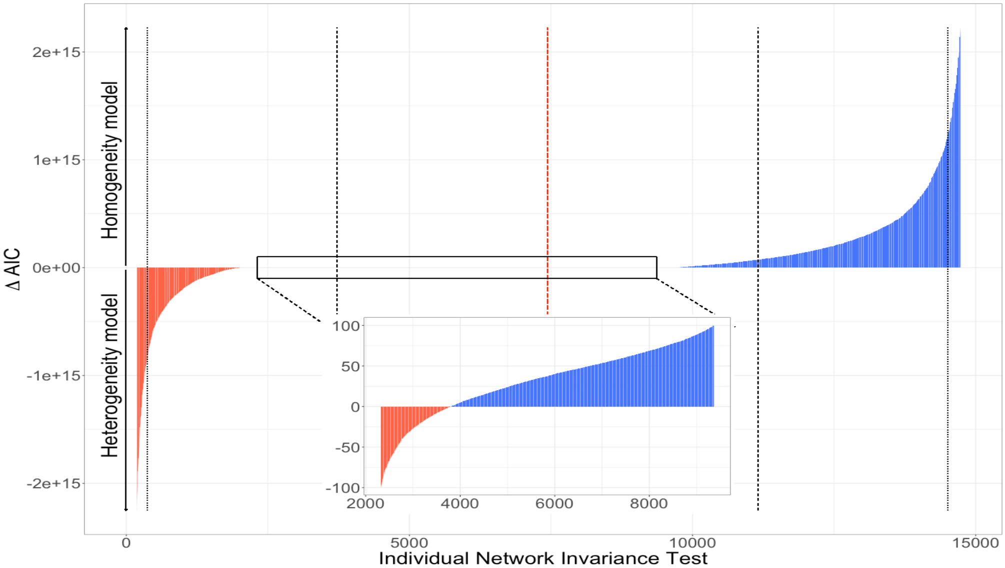
The presented results suggest that nomothetic dynamic networks were robust. Regarding the generalizability results, the constrained model fitted reasonably well in most individuals (72.83%). However, it did not fit well for the rest of the participants. Moreover, the number of participants for whom the constrained model fitted well might be smaller, as false positives might have spuriously improved the goodness of fit of the constrained model. Finally, the heterogeneity analyses showed that estimated networks differed across individuals, which suggests that our sample was heterogeneous.

Robustness of dynamic networks

The presented bootstrapping analyses showed that, with the exception of a few edges, the presented mlVAR's temporal and contemporaneous networks were robust. It cannot be concluded that mlVAR models are robust in general because the robustness of

Figure 3.

Distribution of AIC differences



Note. ΔAIC = $AIC_{heterogeneous}$- $AIC_{homogeneous}$. A positive ΔAIC value means that the homogeneous model has a better fit. A negative ΔAIC value means that the heterogeneous model has a better fit. The red dashed line represents the median, the black dashed lines the 0.25 and 0.75 quantiles, and the dotted dashed line the quantiles 0.025 and 0.975. The zoomed-in plot represents the ΔAIC scores between-100 and 100. Each column represents a comparison between networks of two individuals.

mlVAR models depends on multiple things. For example, the true network, specific processing or analytical decisions, the number of between- and within-individual data points, or the number of nodes included in the model (Mansueto et al., 2023). Therefore, the presented results only apply for models estimated on a similar number of nodes, datapoints and participants. Researchers interested in using mlVAR models are encouraged to perform the presented analyses as exploring the robustness of effects is vital given how frequent underpowered studies and violations of the normality assumption are (Blanchard et al., 2022).

Moreover, researchers are encouraged to explore robustness in different ways. In the present study, robustness was studied by introducing variability at the between-individual level (i.e., in each iteration a proportion of individuals were removed). However, future research could remove chunks of data within-individuals, or a combination of chunks of data within-individual and whole individuals (Epskamp, 2020).

Generalizability from nomothetic to idiographic networks and heterogeneity of individual networks

The generalizability analyses showed that most individuals had a better with the constrained model. This could be because individuals' data is generated from similar data-generating mechanism (i.e., individuals share the same processes). Moreover, the results suggest that mlVAR models effectively capture and summarize these mechanisms. However, follow-up analyses suggests that the apparent goodness of fit for the constrained model might be spurious. In the constrained model, the effects of the nomothetic model were forced to assess their fit with each individual's data, which may have resulted in false positives. This is suggested by the higher proportion of very small but significant effects (i.e., between-0.05 and 0.05) in the constrained model. These effects likely would not have been significant without being forced. Including these effects was necessary to evaluate the generalizability of the nomothetic model to idiographic models, which might have artificially improved the constrained model's fit, leading to an unfair comparison. Therefore, while the nomothetic model appears generalizable to most individuals, the extent of this generalization may be overestimated.

Even with such an unfair comparison, a large proportion of individuals displayed a better fit for the unconstrained model. This suggests that the nomothetic model did not translate optimally even though the comparison favoured such model. Moreover, the heterogeneity analyses suggest that a large proportion of individuals displayed different network structures. This suggests considerable inter-individual heterogeneity dut to different data-generating mechanisms (i.e., individuals display different processes). Together with the generalizability results, while the nomothetic model was generalizable to most individuals, but a number of individuals were not well represented by this model, possibly due to inter-individual heterogeneity.

A relevant avenue for future research is establishing a fairer comparison between the unconstrained and the constrained model. For example, this could be to take out the smallest effects in the constrained model until both the unconstrained and the constrained model have the same number of significant effects. However, it could be argued that with this approach the constrained model does not represent the true constrained model anymore. Alternatively, simulation studies could replicate the presented generalizability analyses with simulated data of individuals coming from the same model (homogeneous individuals) and from different models (heterogeneous individuals). Such a study would show what is the expected EBIC difference or what percentage of individuals display a better fit for each model when the sample is homogeneous and when the sample is heterogeneous. Based on these results it will be easier to draw conclusions if these analyses are applied to real data.

The limited generalizability of the nomothetic model together with the heterogeneity results show the urgency of finding criteria to define homogeneous groups. Such homogeneous groups are needed because nomothetic findings from heterogeneous groups might not be applicable to the individuals composing such group. Only when nomothetic research is carried out using homogeneous groups the findings are applicable to all individuals in that group (Molenaar & Campbell, 2009). Usually, diagnostic criteria are used to create homogeneous groups based on a diagnostic label, such as Major Depressive Disorder (MDD). However, it has been shown that there is large inter-individual heterogeneity is symptom profiles among people sharing the same diagnosis (e.g., MDD; Fried et al., 2020; Fried & Nesse, 2015) (Fried et al., 2020; Fried & Nesse, 2015). More specifically, the unique MDD profiles based on symptom combinations were studied in 3,703 depressed outpatients. The most frequent profile was shared by only 2% of individuals, and 14% of individuals had unique profiles not shared by anybody else. Finally, 86.2% of profiles were shared by 5 individuals or fewer. These findings align well with the results of the current study, similarly pointing to large inter-individual heterogeneity, even when the people in the group share the same diagnosis.

Identifying more homogeneous groups may eventually improve the effectiveness of psychological treatments. Currently, the success of psychological treatments is modest overall (Holmes et al., 2018; Reynolds et al., 2012), and people who recover relapse frequently (Clark, 2018; Layard & Clark, 2015; Roefs et al., 2022). That might be because treatments are developed based on mechanistic research carried out at the nomothetic level. It is known that nomothetic research is only translatable to all the individuals in a sample under strict conditions that are rarely met, such as homogeneity of the sample (Molenaar & Campbell, 2009). Therefore, finding homogeneous groups is vital for nomothetic research to be insightful about individuals (Molenaar & Campbell, 2009) and, consequently, finding more effective psychological treatments for individuals.

Integrating findings from idiographic research with traditional nomothetic approaches can lead to a more comprehensive understanding of psychological processes and may help finding homogeneous groups. First, nomothetic bottom-up approaches, such as clustering methods that align with network analysis methods, may be able to identify more meaningful subgroups with similar network structures. One such clustering method is the subgrouped chain graphical VAR (scGVAR; Park et al., 2024) (Park et al., 2024). However, the number of subgroups using scGVAR needs to be predefined. Second, idiographic top-down research could investigate possible indicators of homogeneous groups such as theory-driven mechanisms from a network perspective. If specific mechanisms are relevant for some individuals and not for others, such mechanisms may be a good criterion for identifying a homogeneous group. For example, individuals' mood or anxiety problems may arise from different coping mechanisms (e.g., avoidance or substance abuse) that are motivated by different thoughts, and reinforced by different appraisals. Therefore, different coping mechanisms, appraisals of situations, or thoughts might be relevant criteria to identify homogeneous groups.

Top-down approaches can be used with small samples to validate potential mechanisms that might be relevant indicators of homogeneous groups. There are a number of ways to validate such mechanisms from a network approach using idiographic research. For example, investigating whether the networks of people with similar coping mechanisms, thoughts and appraisals display the same structure. Analyses such as the INIT (Hoekstra et al., 2024), mlVAR group comparison (Haslbeck et al., 2023), or single case experimental designs (Vlaeyen et al., 2022) could assist with this purpose. Once some potential homogeneous groups have been identified, the data of a number of different homogeneous groups can be fed to scGVAR. Since the number of groups is known a priori, scGVAR can confirm whether a clustering solution with the defined number of groups has a good fit. Moreover, it can be confirmed whether the individuals that were thought to belong to the same group cluster together.

It is important to note that both bottom-up and top-down approaches may benefit greatly from using lower-level networks (Jover Martínez, Lemmens, Fried, Haslbeck, et al., 2024). Lower-level networks move the focus from a broad range of psychological problems to specific processes such as the relations between specific thoughts, motivations, coping mechanisms, and outcomes thereof. For example, two individuals may show the same behavior but the behavior might be differently motivated. Consider going for a run. A person might engage in such behaviour because they are motivated to live a healthy lifestyle. This could lead to positive thoughts, and an improved mood. However, another person might go for a run because they ate one too many cookies, which leads to weight gain related thoughts, which leads to anxiety. The same behaviour is motivated in very different ways, and this difference in motivation could be clinically relevant. These types of networks are valuable because they may be the building blocks of higher-level networks (Wichers et al., 2021). Higher-level networks might be useful to map relevant processes, but not to fully understand them. Zooming in on lower-level networks might be more informative for specific processes and a better guide to the treatment that is needed.

Conclusion

This study investigated the robustness, generalizability, and heterogeneity of psychopathology networks. When using case-dropping bootstrap, temporal and contemporaneous mlVAR networks can be robustly estimated. The generalizability from nomothetic to idiographic networks is limited. This could be due to the heterogeneity in the sample as supported by the presented heterogeneity analyses. Moving away from clinical diagnoses and finding valid indicators of homogeneous groups is vital to draw conclusions on the generalizability and heterogeneity of network models. To find such groups, a combination of bottom-up clustering approaches, like subgrouped chain graphical VAR (scGVAR) models, and top-down theoretically-driven approaches, like exploring mechanisms underlying psychopathology, is suggested. For this, it is emphasized that single-case research on lower-level networks might be optimal to do such research, and can ultimately contribute to more effective treatments for mental disorders.

Chapter 6

Overview of empirical findings, general discussion and conclusion

In this thesis two main aims were pursued. The first aim was developing tools to measure psychopathology from a transdiagnostic perspective in daily life. Previous research shows that long questionnaires lead to low compliance and high perceived burden in EMA studies (Eisele et al., 2022). This makes it difficult to study broad concepts like transdiagnostic psychopathology in EMA studies, as studying these concepts requires long questionnaires. Moreover, estimating dynamic network models reliably requires a large amount of data, with more nodes in an estimated network requiring increasingly more data (Mansueto et al., 2023). For that reason, EMA studies with network modelling purposes must last long enough to gather sufficient data. Therefore, the development of an EMA protocol to assess transdiagnostic psychopathology in daily life of acceptable length and with limited perceived burden was a priority (Chapter 2).

As a next step, the questionnaire was administered in a 28-days EMA protocol in a sample of 262 students to study its feasibility. Specifically, the participants' subjective experience, compliance, dropout, and associated variables were studied. Moreover, the between- and within-individuals variability of the items were studied, as an assumption of longitudinal data is that it captures fluctuations in the variables of interest (Schreuder et al., 2020). Finally, the association of the EMA items with baseline standard questionnaires of psychopathology was investigated, to obtain measures of convergent and divergent validity (Chapter 3).

The second aim was studying networks of transdiagnostic psychopathology from different angles. First, it was investigated whether the network structures of individuals with different levels of psychopathology are different. Network theory hypothesizes that dynamic intra-individual networks of healthy individuals are different from networks of individuals suffering from psychopathology (Borsboom, 2017). Specifically, networks that are more strongly connected are theorized to reflect a psychopathological state, whereas weakly connected networks are theorized to reflect a healthy state (Borsboom, 2017; Wigman et al., 2013, 2015). The reasoning behind this is that in highly connected networks node activation can quickly spread and activate other nodes, while in weakly connected networks this is not the case as nodes are not connected. Therefore, we hypothesized that connectivity in estimated dynamic networks would be higher in people with higher psychopathology levels (Chapter 4).

Second, the robustness of these dynamic networks was investigated. Robustness is a vital property of network models (Blanchard et al., 2022). If statistical estimates are susceptible to slight variations of the data – that is, are not robust- estimated networks are unreliable (Ševljakov & Vilčevskij, 2002). However, the robustness of dynamic networks has barely been studied (Blanchard et al., 2022). Therefore, a non-parametric bootstrapping method was used, where 75% of the sample was drawn with replacement in 100 permutations. In each iteration, an mlVAR model was fitted, resulting in a distribution of every effect between the network's nodes. By introducing a variation of the data (i.e., only sampling a part of the participants) it was possible to study how consistently the effects were estimated (i.e., how robust the model was).

Third, whereas the network theory is idiographic in nature, most research is done at the nomothetic level (Robinaugh et al., 2020; Wichers et al., 2021). Importantly, processes derived from nomothetic research are generalizable to individuals only under rarely met conditions (i.e., ergodicity). Specifically, individuals composing a group must be homogeneous so that results are generalizable to all individuals in the group (Molenaar & Campbell, 2009). This might threaten the generalizability of many conclusions in the field of psychology as such conditions are rarely met (Fisher et al., 2018). Therefore, the generalizability of a nomothetic network model (i.e., mlVAR) of transdiagnostic psychopathology to idiographic models (i.e., graphicalVAR) was investigated (chapter 5).

Finally, the potential lack of generalizability can be due to the heterogeneity of the people included in the sample. In other words, nomothetic models might not generalize to all individuals in a sample because these individuals are too different. Moreover, whereas some authors argue that idiographic network are very heterogeneous (Beck & Jackson, 2020; Levinson et al., 2023; Piccirillo & Rodebaugh, 2022; Reeves & Fisher, 2020), others argue that such heterogeneity might just be due to sampling variation (Hoekstra et al., 2023). Therefore, the heterogeneity of idiographic models was studied. Specifically, the Individual Network Invariance Test (INIT), based on principles of invariance testing, compares if networks of two individuals come from the same model when estimated freely, and when estimated under the assumptions that the network parameters are the same (Hoekstra et al., 2024).

Main findings

Aim 1. Developing tools to measure psychopathology from a transdiagnostic perspective in daily life.

In the first study, an EMA protocol to assess psychopathology from a transdiagnostic perspective was developed (chapter 2). Specifically, an online survey of clinicians and 12 focus groups with clinical experts provided input for EMA items for the disorders they specialized in. Next, this input was coded by independent raters, and a selection was reached by consensus. The resulting protocol consisted of 35 momentary, 26 daily, and 4 weekly EMA items, and tapped a broad range of variables reflecting psychopathology, such as mood, anxiety, trauma and stress, or personality disorders (for an overview of the EMA items see https://osf.io/qk85a).

Strikingly, there was considerable overlap between the EMA items mentioned by the clinicians for the different categories of mental disorders. For example, Jaccard similarity indices showed a 53% overlap between the items proposed by the therapists specializing in trauma- and stress-related disorders and those specializing in anxiety disorders; a 48% overlap between those specializing in personality, and those specializing in trauma- and stress-related disorders; and a 47% overlap between those specializing in anxiety and those therapists specializing in neurodevelopmental disorders. Due to this overlap of symptoms across DSM-5 categories, the number of items to be included in the EMA protocol could be kept within reasonable limits. This substantial overlap aligns with a study that showed that the overlap between DSM categories is so extensive that the criteria of some diagnoses are composed entirely of criteria for other diagnoses (Forbes et al., 2024). More specifically, though 397 symptoms of 628 identified symptoms (63.2%) were specific to a single diagnosis, 231 symptoms (36.8%) appeared in multiple diagnoses, collectively recurring 1022 times (with a median of 3 occurrences per symptom and a range from 2 to 22). Strikingly, the criteria of some diagnoses (e.g., bipolar disorders) consisted entirely of repeated symptoms. Thus, the DSM-5 categories may be poorly delineated, as psychopathology is transdiagnostic in nature, enabling a wide range of phenomena to be measured with few items in EMA settings.

Chapter 3 describes a 28-day EMA study in a sample of 262 students with varying baseline psychopathology. Specifically, the participants' subjective experience, compliance and dropout levels, and reliability and validity of the developed EMA questionnaire was investigated. Moreover, the within- and between-individuals variability was investigated, and the association of the EMA items with baseline measures of psychopathology was studied.

Participation in this 28-day protocol was considered acceptable. Participants rated the protocol as being somewhat influential on participants' daily lives, and somewhat frequent. The questions were clear and neither easy nor difficult to complete, and the study was neither too burdensome nor too light. Other studies have found that their protocol was less burdensome, possibly due to shorter duration (Eisele et al., 2022). Male participants reported less influence of the protocol on their lives. Participants with higher psychopathology felt more burdened, had more trouble completing surveys, and found the study period less representative of their lives. These findings align with studies showing less compliance in people with a mental health diagnosis (Jones et al., 2019; Rintala et al., 2020; Vachon et al., 2019). Missing surveys, leading to less compliance, could be an attempt to reduce burden (Eisele et al., 2022; Stone et al., 2003). Therefore, the presented protocol should be adapted for different populations, such as reducing the workload for clinical populations. For example by triggering fewer surveys per day, or by shortening the study duration.

Dropout mostly occurred in the first week and was not associated with any studied predictor. Average compliance was 67%, with no personal characteristic significantly associated with it. This contrasts with studies showing higher compliance in females (Rintala et al., 2019; Vachon et al., 2019; Wrzus & Neubauer, 2023). Some authors suggest gender-compliance differences may arise from interactions between gender and design variables (Wrzus & Neubauer, 2023). For example, gender differences might be mitigated by the number of assessments or rewards included. Regarding psychopathology, unlike the present results, other studies found varying compliance among healthy participants, those with psychosis, and those with depression (Rintala et al., 2019, 2020; Vachon et al., 2019). That might be because this study examined overall psychopathology levels in a non-clinical sample rather than clinical diagnoses.

Some time, design and momentary characteristics were associated with compliance levels. Surveys were more likely to be missed on Mondays, Sundays, and later study days, confirming previous findings that compliance declines over time (Rintala et al., 2019, 2020; Vachon et al., 2019; Wrzus & Neubauer, 2023) and that identified Sundays as the second-least compliant day (Rintala et al., 2019). Concerning design factors, longer and less rewarded surveys had lower compliance, consistent with studies showing higher compliance for shorter surveys and greater rewards (Eisele et al., 2022; Wrzus & Neubauer, 2023). Finally, participants were less likely to respond if they had high positive affect at the previous time point or missed the previous survey. Another study also found that participants were more likely to miss a survey after consecutively missing multiple beeps, but less likely if they experienced positive affect at the previous time point (Rintala et al., 2020).

Both within-individuals and between-individuals variability differed across EMA items. Most EMA items exhibited greater variability between individuals than within individuals. Contextual factors (e.g., the number of people one is with) had the highest within-individual variability, while extreme behaviors (e.g., self-harm) had the lowest. Low within-individual variability might be due to floor effects, as items with low variability also had low means. This might not apply to populations that frequently engage in these behaviors. An alternative explanation is that items with low variability may change slowly, suggesting the protocol measured them more frequently than the time needed for change.

Most EMA items correlated quite extensively with baseline measures of psychopathology, though a few EMA-items (e.g., avoidance- or sex-related items) showed fewer correlations. Even disorder-specific items, like body-checking, correlated with multiple baseline questionnaires, which could suggest poor construct validity or highlight the transdiagnostic nature of psychopathology and the poor delineation of DSM-5 categories. EMA items generally correlated with transdiagnostic baseline measures as well. Those EMA items with fewer correlations with disorder-specific questionnaires also showed fewer correlations with transdiagnostic questionnaires. While correlations were consistent in direction across baseline measures, they were opposite for personality trait measures (e.g., extraversion, agreeableness, conscientiousness, emotional stability, openness). For instance, negative mood EMA items correlated positively with baseline measures of psychopathology but negatively with personality traits, a pattern consistent across all EMA items. This is reasonable as, unlike the rest of the baseline measures, such personality traits are not psychopathological.

Aim 2. Studying networks of transdiagnostic psychopathology

Chapter 4 shows how the gathered EMA data was used to compare the structure of networks of transdiagnostic psychopathology between groups with different levels of psychopathology. It was hypothesized that the structures would differ and that the group with higher psychopathology levels would display a more interconnected network (i.e., higher connectivity). However, the difference in connectivity between a group with higher versus lower baseline psychopathology was small, and only a few edges were significantly different between groups. Literature regarding the connectivity hypothesis is inconsistent, with some studies finding evidence in favor of it and others not (Wichers et al., 2021). All studies investigating the connectivity hypothesis in depression which found evidence in favor of such hypothesis (De Vos et al., 2017; Pe et al., 2015; Wichers et al., 2016, 2020; Wigman et al., 2013, 2015) except one (Wigman et al., 2013) included participants with a clinical diagnosis of Major Depressive Disorder diagnosis. Therefore, our results might not be in line with the connectivity hypothesis because we compared two non-clinical groups, although they differed significantly on psychopathology levels.

Another explanation is that though the relationships between nodes are similar in both high and low psychopathology populations, the systems operate at different levels. Specifically, in the higher psychopathology group, the average scores on the nodes were significantly higher than in the lower psychopathology group. To give an example, independent of the level of psychopathology, worry at time point t – 1 might predict sad mood at time point t, but the average levels of both worry and sad mood are increased in participants with a higher level of psychopathology. So, this means people scoring higher on psychopathology will feel more worry and sadness, but the relationship between worry and sadness is the same across psychopathology levels.

Relatedly, network theory (Borsboom, 2017; Scheffer et al., 2024) suggests that a person can move from a healthy to an unhealthy state when external events activate (a) certain node(s). This activation can cause a cascade effect, forming highly connected networks (Borsboom, 2017). These new connections remain active even after the external event ends, a phenomenon known as network hysteresis (Borsboom, 2017). However, it could be that hysteresis occurs because node levels remain high after the connections disappear, rather than due to the maintenance of new connections after the trigger has disappeared. In other words, it could be that the transition from a healthy to an unhealthy network is not reflected in different network structures, but in different node levels. Only during the transition new edges emerge that raise the node levels. Once an unhealthy state has been reached, the edges disappear and the means stay high, leaving a network structure similar to a healthy network, but with different node levels.

Finally, the variables included in the networks mostly reflect symptoms of psychopathology, not mechanisms underlying psychopathology. This choice of variables, reflecting mostly symptoms, is in line with network theory (Borsboom, 2017) and most empirical research does likewise (Robinaugh et al., 2020; Wichers et al., 2021). However, The DSM-5 categories do not imply that symptoms included in one category are provoked by a common causal mechanism (Kajanoja & Valtonen, 2024). Therefore, by focusing almost exclusively on symptoms it will be difficult to identify the causal relations that provoke mental health problems and need to be treated.

To study causal mechanisms of psychopathology, variables such as behaviors, cognitions, and contexts should be included (Bringmann, 2024). This selection of variables is in line with functional behavioral analysis, a therapeutic framework that aims to understand psychopathology as causal relationships between behaviors (Haynes & O'Brien, 1990). Clinical experts have already suggested including variables that reflect functional behavioral analysis in network models (Schemer et al., 2023), as this framework dovetails nicely with the network approach to psychopathology and might help unveiling what causes symptomatology (Hofmann & Hayes, 2019). Relatedly, psychopathology might not be reflected in network structures on the number of edges or the connectivity levels.

Instead, psychopathology might be reflected on specific relevant edges. In other words, the network structure of a person with mental health problems might display one specific edge that the network structure of another person without mental health problems might not display. Symptom networks might not capture such specific relevant edges, but variables that reflect functional behavioral analysis addressing specific pathological mechanisms might. Such specific edges could be used as indicators of differing levels of psychopathology.

In chapter 5, the robustness, generalizability, and heterogeneity of dynamic networks were investigated. First, it was shown that both the temporal and contemporaneous nomothetic networks were estimated robustly. In other words, the effects of these networks did not change significantly when they were re-estimated with only a part of the sample.

Second, the generalizability of a nomothetic network model (i.e., mlVAR) to an idiographic network model (i.e., graphicalVAR) was investigated. The network structure of the nomothetic model was generalizable to most individuals. However, a proportion of participants (27.17%) were not well represented by the nomothetic model. Moreover, the constrained models (i.e., idiographic network models in which the significant effects from the nomothetic network model were restricted) were forced to estimate the effects found in the nomothetic models. That analytical approach may have artificially improved the goodness of fit of the constrained models, putting the unconstrained models at a disadvantaged comparison. Therefore, the proportion of individuals that were well represented by the nomothetic model may be less than the presented results suggest, highlighting the need for intra-individual research (Fisher et al., 2018).

Finally, the heterogeneity among estimated dynamic individual networks was investigated. A large proportion of individuals' network structures were different from one another, and such differences were not due to sampling variability. This aligns nicely with the generalizability results as one condition for nomothetic models to generalize to individuals is that the group is homogeneous (Molenaar & Campbell, 2009). Moreover, it aligns well with a number of studies that concluded that idiographic models are highly heterogeneous (Beck & Jackson, 2020; Levinson et al., 2023; Piccirillo & Rodebaugh, 2022; Reeves & Fisher, 2020).

Conclusions

1. The same EMA items were chosen for different categories of mental disorders, suggesting that psychopathology is transdiagnostic in nature (chapter 2).

Moreover, most EMA items correlated with a diverse set of baseline questionnaires of psychopathology. This was even true for disorder-specific EMA items such as body checking (chapter 3). These findings are in line with research showing the extensive overlap between DSM-5 categories (Forbes et al., 2024), which – considering the absence of well-defined etiologies of mental disorders – also points towards the transdiagnostic nature of psychopathology and the limited validity of DSM-5 categories.

2. Studying broad concepts, such as transdiagnostic psychopathology, for purposes that require many data points, such as network-modelling, is possible (chapter 3). Feasibility is helped by the transdiagnostic nature of psychopathology (see conclusion 1) as it reduces the number of EMA items that are required to cover the full range of psychopathology. Moreover, perceived burden, compliance and dropout were acceptable (chapter 3). However, adjustments in the protocol might be necessary if used in clinical populations.
3. The EMA items showed within- and between-individual variability (chapter 3). Some items displayed low variability at both the within- and the between- level, which could indicate that these constructs change more slowly over time, or floor effects (Schreuder et al., 2020).
4. Networks of transdiagnostic psychopathology between students with different levels of psychopathology were similar regarding edges and connectivity (chapter 4). Differences in networks between individuals scoring higher versus lower on baseline psychopathology might not be a matter of differential connectivity but of symptom severity.
5. Nomothetic temporal networks can be estimated robustly (chapter 5). However, due to the heterogeneity of idiographic networks, the results from nomothetic networks are not fully generalizable to all individuals (chapter 5). Therefore, more idiographic research is needed for investigating psychopathological mechanisms, and improving clinical practice (Bringmann, 2024).

Future directions

Ecological Momentary Assessment

Based on the results presented in chapter 3, future research should investigate if the presented EMA protocol is feasible in different populations. The goal of the network approach is to explain psychopathology and ultimately improve clinical practice (Borsboom, 2017; Bringmann, 2024). Therefore, more research in clinical populations is needed. The burden and compliance of this type of EMA protocols in these populations should be investigated. Skip logics, which ensure that items only relevant to the population are triggered to reduce questionnaire length is a possibility. Another possibility is to trigger surveys fewer times per day while lengthening study duration so that workload is spread across time reducing the intensity of the protocol. In addition, it should be investigated if the results of the current sample generalise to male participants, considering that our sample was predominantly female.

Assessment frequency is also determined by the timescale on which the studied variables unfold. Ideally, the chosen assessment frequency should represent well the way a variable unfolds with the minimum number of measurements possible. However, the true way a variable unfolds is unknown. One approach to decide assessment frequency could be choosing one that maximizes the captured variance. For example, if measuring a specific variable every two hours leads to more within-individual variability than measuring it every hour, the former timescale might be preferred. This type of research might also shed some light on what enough variance is. Another approach might be using autocorrelation functions. Autocorrelation functions check the correlations between the observations of a variable's time series for a set of lags (Box et al., 2016). If the lag with better fit for a variable is a lag-3, and such variable was assessed every hour, assessing such variable every three hours might be a better solution.

It is likely that different variables (e.g., mood and sleep) need to be assessed at different frequencies. However, this practice is uncommon as up until recently there were no available methods to integrate variables measured at different frequencies. One recently developed option is the Kalman filter (Durbin & Koopman, 2012; Kalman, 1960). The Kalman filter predicts the next time point based on previous data and updates its predictions when new information is available. If no new observation is available (i.e., due to missing data), it retains its previous prediction. This ensures that no observations are lost, even when some time points are missed due to different assessment frequencies (Bringmann et al., 2024). Another promising option is using multi-layered networks (Blanken et al., 2021), with each layer consisting of a network of variables unfolding at a specific time frequency, going from most frequent (bottom layer) to least frequent (top layer). Edges are estimated between layers, reflecting co-variation between the networks reflecting different timescales. However, this method is only possible from a nomothetic approach, as a distribution of relations between nodes, and node level is needed to estimate covariation between layers.

Network approach

Chapter 4 revealed few significant differences between the networks of students with higher versus lower levels of baseline psychopathology. However, an open question is whether people with a diagnosis of a mental disorder will be characterized by a different network structure. Moreover, the networks were compared edge by edge. Therefore, it is not known if the overall network structure is different. There are methods available to compare overall network structures (Hoekstra et al., 2024). However, such methods only work with idiographic models. Thus, models to compare overall nomothetic networks are needed to test if overall network structure of such models differ.

Regarding the lack of differences on connectivity levels, standard operationalization was used (i.e., the sum of the absolute values of all the network's edges; Epskamp et al., 2018). However, our model includes variables that would benefit participants if they were highly connected (e.g., positive affect). In that case, connectivity would not indicate a pathological state. Moreover, the direction of the connections would also play a role, but directionality is disregarded as only the absolute values are used. For example, if a network only displays connections towards positive affect, such network might be healthy and display high connectivity. However, whether such network is healthy or not will depend on the direction of the connections. If the connections are positive (i.e., increase positive affect), the network will be healthy, but if they are negative (i.e., decrease positive affect), the network will be unhealthy. Therefore, new ways of studying connectivity, which consider the meaning of the nodes and the direction of the edges, are needed.

Robustness of networks could be studied from different angles. In chapter 5, a case-dropping bootstrap method showed that the temporal and contemporaneous effects were estimated robustly despite variations in the data. Instead of dropping whole cases, an alternative approach is dropping a sequence of time series data per participant (Epskamp, Borsboom, et al., 2018). Another option would be studying robustness when both whole cases and sequences of time series data are dropped. In this case, the robustness of the model would not only depend on power at the between-individuals level, but also on power at the within-individual level.

In Chapter 5, the goodness of fit for an idiographic model, where effects matched those of a nomothetic model, was compared to an unconstrained model, where effects were freely estimated. However, the goodness of fit differences were simply subtracted without a parametric test determining if the differences were significant. Similarly, it is unclear for what proportion of individuals the constrained model should be preferred if the nomothetic model is generalizable, or the unconstrained model if it is not. Simulation studies are needed to clarify expected results when a model is generalizable or not. These studies could create two conditions: one where simulated individuals meet the criteria for a generalizable nomothetic model (homogeneity and data stationarity), and one where they do not. This can be done by simulating individuals from the same model in the first condition and from different models in the second. The analytical routine from Chapter 5 can then determine the threshold for goodness of fit and the proportion of individuals preferring each model in each condition.

Chapter 5 highlights the high heterogeneity among individual networks. Similar issues to the generalizability results are encountered. The goodness of fit for different models was simply subtracted without a parametric test to determine if the difference was significant. A similar simulation study with two conditions could be conducted: one with homogeneous individuals (coming from the same model) and one with heterogeneous individuals (coming from different models). Comparing individuals within each condition would reveal what proportion of individuals are the same or different based on whether they came from the same data-generating mechanism

It is relevant to note that issues regarding generalizability and heterogeneity are directly related to the possibility of identifying homogeneous groups in the field of psychopathology. Specifically, for nomothetic models to be generalizable to all units in the sample, such units must be homogeneous (Molenaar & Campbell, 2009), and heterogeneity is the opposite of homogeneity. Samples are rarely homogeneous when studying psychopathology (Fisher et al., 2018; Molenaar & Campbell, 2009), likely because the indicators used to identify homogeneous individuals are invalid as they do not lead to homogeneous samples. For example, a DSM-5 diagnosis, often used for sample selection, lacks validity and leads to heterogeneous groups.

Future research should aim to identify reliable indicators of homogeneous groups. Relevant psychopathological mechanisms that provoke the symptoms might serve as indicators. The DSM-5 lists symptoms together under clinical diagnoses, which is frequently interpreted as the diagnoses representing a latent factor that causes the symptoms (Kajanoja & Valtonen, 2024), but the DSM-5 does not indicate that such diagnoses are the causes of the symptoms, and “a complete description of the underlying pathological processes is not possible for most mental disorders” (American Psychiatric Association, 2013, p. xi). This absence of mechanisms provoking the symptoms could be the reason why DSM-5 diagnoses lead to heterogeneous groups, as two individual might experience the same symptoms due to different causes. Therefore, identify mechanisms that provoke symptoms might be needed to identify homogeneous groups.

The network approach is also opposed to the view that a latent factor represented by a diagnosis provokes symptoms, which opens the possibility of finding symptom-provoking mechanisms. However, the focus of the network approach has so far been almost exclusively on symptoms, both theoretically (Borsboom, 2017) and empirically (Robinaugh et al., 2020; Wichers et al., 2021). Symptoms are conceptually dependent on their clinical diagnoses (i.e., the symptoms are the diagnoses; Borsboom & Cramer, 2013; Kajanoja & Valtonen, 2024). Therefore, by focusing on symptoms, one still focuses on the diagnoses and, consequently, current research on the network approach to psychopathology is biased by the DSM-5. Moreover, by only focusing on symptoms, the causes of such symptoms cannot be identified. In other words, relevant mechanisms might be overlooked if variables other than symptoms are not studied (Bringmann, 2024; Kajanoja & Valtonen, 2024). Future research from the network approach should focus on variables other than symptoms to step away from the medical model of psychopathology and the DSM-5, find symptom-provoking mechanisms, and study if such mechanisms lead to homogeneous groups.

Functional behavioral analysis-based variables, such as context, cognitions, and behavioral responses, might help identify such mechanisms (Bringmann, 2024; Hofmann & Hayes, 2019; Schemer et al., 2023) as functional behavioral analysis understands psychopathology as causal relationships between behaviors (Haynes & O'Brien, 1990). Mechanisms based on this type of variables could serve as better indicators of homogeneous groups than DSM-5 diagnoses. First, functional behavioral analysis is often used to decide the specific intervention for a client (Emmelkamp, 1986; Haynes et al., 1986; Haynes & O'Brien, 1990). Therefore, unlike with DSM-5 diagnoses, groups based on treatment needs could be determined based on such mechanisms. Second, these indicators would provide a worked-out mechanism provoking an individual's symptoms. This aligns with some medical diagnoses, which already imply an etiology pneumococcal pneumonia or cell carcinoma of the lung (Borsboom & Cramer, 2013; Hyman, 2010; Maung, 2016). Note that for many medical diagnoses, no worked-out etiology is available either, such as juvenile arthritis or idiopathic atrial fibrillation (Tirlapur et al., 2013). Finally, the mechanism explains the symptoms causally, unlike DSM-5 diagnoses which merely group symptoms together, without addressing their causes.

Other authors theorize that networks of lower-level variables are the building block of symptom networks (Wichers et al., 2021). Using mechanisms as indicators of psychopathology aligns with this way of thinking, in that lower-level networks might reflect mechanisms that provoke symptomatology in higher-level networks. In this way, lower-level networks capturing mechanisms would build up higher-level network reflecting symptomatology. Finally, if the proposed mechanisms lead to homogeneous groups, one of the conditions for nomothetic research to be generalizable to individuals (i.e., group homogeneity) would be met (Molenaar & Campbell, 2009). Therefore, the generalizability of results based on nomothetic research would not be threatened (Fisher et al., 2018).

To validate candidates of network-derived mechanisms, two approaches can be taken. First, an idiographic approach where the networks of individuals with the same and different mechanisms are compared. If networks of individuals engage in the same mechanisms are consistently similar, it suggests these mechanisms indicate homogeneous groups. Conversely, consistently different networks for different mechanisms suggest the same. Such comparisons could be done using the Individual Network Invariance Test (Hoekstra et al., 2024). From a nomothetic approach, groups of individuals engaging in different mechanisms could be clustered to see if clustering solutions align with the a-priori determined number of groups. For example, if four mechanisms are identified a priori, the individuals' networks reflecting such mechanisms could be clustered, and different cluster solutions could be compated (e.g., two clusters, three clusters, four clusters, etc.). If the four clusters solutions has the best fit, it would suggest that the mechanisms are reliable indicators of homogeneous groups. Moreover, if the clustering algorithm groups individuals together and such groups overlap with those composed a priori, similar conclusions could be drawn. There are methods already available to carry out this analyses, like subgrouped chain Graphical Vector Autoreggression (Park et al., 2024).

Concluding remarks

Studying broad concepts in EMA studies with network modelling purposes was shown to be feasible, but methods to integrate variables measured at different timescales is urgent for networks to be comprehensive. Moreover, network structures of students with differing levels of psychopathology do not differ significantly despite significant differences in average severity. However, this could be due to the population of study. Therefore, more work in clinical populations is needed to determine the usefulness of the network approach in the understanding and treatment of mental health problems. Furthermore, the network approach to psychopathology might benefit from including variables other than symptoms, as such variables might capture relevant mechanisms that capture psychopathology, and are indicators of homogeneous groups.

Appendix

Impact Addendum

Mental disorders are one of the major current public health problems of our time (Cuijpers, 2019; Lopez & Murray, 1998). Hundreds of millions and their relatives are affected globally, leading to considerable financial costs (Bloom et al., 2012), increased physical illness, and mortality (Cuijpers et al., 2014; Liu et al., 2017). Moreover, mental disorders are transmitted transgenerationally (National Research Council (US) and Institute of Medicine (US) Committee on Depression, Parenting Practices, and the Healthy Development of Children, 2009; Reupert et al., 2013).

Treatment success is modest at best in the short and long term across disorders (Clark, 2018; Holmes et al., 2018; Layard & Clark, 2015; Reynolds et al., 2012; Roefs et al., 2022). Many people with mental health problems do not receive treatment, and about 60% of the ones who receive it do not respond to it or relapse within a year (Clark, 2018; Layard & Clark, 2015). Moreover, treatment effect sizes of the currently dominant psychological treatment (i.e., cognitive behavior therapy) are moderate (Reynolds et al., 2012). This lack of treatment success suggests that there is a limited understanding of what mental disorders are,how they work, and how they can best be treated (Cuijpers, 2019; Holmes et al., 2014, 2018).

The dominant framework for understanding mental disorders is the medical model, upon which the DSM-5 is based as the main diagnostic system of mental disorders (Cuijpers, 2019; Deacon, 2013). However, DSM-5 diagnoses are criticized for several reasons: no common pathogenic pathways have been found (Borsboom & Cramer, 2013; Kendler, 2012; Kendler et al., 2011), they lack validity (Greenberg, 2014), people with the same diagnosis display highly heterogeneous symptom profiles (Fried et al., 2020; Fried & Nesse, 2015), comorbidity is the rule, rather than the exception (Cramer et al., 2010; Kessler et al., 2005; Kim & Eaton, 2015; Lilienfeld, 2014; Nolen-Hoeksema & Watkins, 2011; Sauer-Zavala et al., 2017), and evidence suggests that mental disorders are not separate entities (Krueger et al., 2014, 2018; Widiger & Samuel, 2005). Therefore, new frameworks are needed to understand and treat psychopathology. This thesis aimed at advancing the network approach to psychopathology as an alternative to the medical model.

The network approach to psychopathology posits that psychopathology does not arise from a latent factor, namely a disorder, provoking the symptoms, but of dynamic interaction between the symptoms. The findings in this thesis demonstrate that studying transdiagnostic psychopathology in EMA studies with network modelling purposes is feasible. Moreover, it advanced the understanding of network structures of transdiagnostic psychopathology. Specifically, potential explanations for network structure differences between individuals with different levels of psychopathology were provided. Finally, the heterogeneity of idiographic networks was confirmed by this thesis. The heterogeneity results, together with the generalizability results, indicates that more idiographic research is urgent. These findings are relevant for research, clinicians, people suffering from mental health problems, and policymakers and insurance companies.

First, regarding research, this thesis provides researchers interested in psychopathology in daily life an EMA protocol that is publicly available and can be used in other studies. Moreover, information about a range of variables that can affect data collection is provided in case adaptations are necessary for different aims. Furthermore, data about a broad arrange of self-reported and passively collected variables was gathered that is being used by other researchers and will be made publicly available in the future. Moreover, this thesis provides a number of explanations regarding the differences in network structure of transdiagnostic psychopathology between individuals with different levels of psychopathology. Finally, insight on the heterogeneity and generalizability results that researchers can build on was provided.

Second, the findings of this thesis have significant implications for clinicians. Our research shows that DSM symptoms often overlap across disorders, and that symptom networks are highly heterogeneous. This underscores the necessity for clinicians to move beyond protocolarized treatments that tackle single disorders. Instead, there is a need for personalized interventions that tackle specific individuals' problems that tap onto a broad range of symptoms. Additionally, this thesis presents an EMA protocol designed to gather valuable insights during waiting periods, supplementing traditional clinical interviews. The data obtained through this protocol can serve as additional input besides clinical interviews, enhance case conceptualization, and serve as a confirmation of clinical hypotheses. By integrating these methods, clinicians can achieve a more nuanced understanding of their patients, ultimately leading to improved therapeutic outcomes.

Third, people with mental health problems can obtain relevant insight from this thesis. Some research suggests that the medical model is frequently misinterpreted by individuals leading to negative consequences (Kajanoja & Valtonen, 2024). Specifically, receiving a diagnosis can make people believe that their problems are provoked by an external pathological process over which they have little or no control. Due to this belief, people may refrain from seeking understanding of their lived experiences, leading to more stigma, less agency, and less adaptive beliefs regarding their symptoms. Chapter 2 shows that DSM-5 diagnoses are not very well delineated as there is considerable overlap between them. This suggests that diagnoses are not good representations of common pathological problems. Therefore, individuals should see such diagnoses as mere descriptions of their symptoms rather than causal explanations. Moreover, chapter 5 shows how heterogeneous individuals can be, and that attributing a clinical diagnosis to people might not reflect such heterogeneity. This should encourage individuals to seek specific explanations regarding their personal life experiences. The presented EMA protocol can help individual get more insights regarding the specific problems.

Finally, this thesis has implications regarding policy makers and insurance companies. Specifically, this thesis may provide information relevant to guide policies regarding clinical practice, and research. First, this thesis suggests that seeing psychopathology as a transdiagnostic continuum reflects reality better than as separated in diagnoses. Consequently, the treatment people receive might be better based on indicators other than clinical diagnoses. Therefore, policymakers should re-consider ways of determining the type and length of treatment people suffering from mental health problems should receive. Moreover, this thesis suggests that mechanisms that can be used as indicators of specific mental health problems are urgent. A network approach to psychopathology can be useful in identifying such mechanisms. However, the emphasis should not be on symptoms or clinical diagnoses. Therefore, policymakers may want to prioritize research from a network approach that studies variables other than symptoms. Moreover, this thesis shows how the high heterogeneity of individuals might threaten generalizability of nomothetics research. Thus, policymakers might want to consider prioritizing idiographic research.

So far, chapters 2 and 3 have been published in the International Journal of Methods in Psychiatric Research and in Psychological Assessment respectively, and chapters 4 and 5 have been submitted to Behaviour Research and Therapy and Clinical Psychological Science respectively. Moreover, all results were presented at national and international conferences, such as the Meeting of the Association of Behavioral and Cognitive Therapy in New Orleans (2021), the European Association of Cognitive Behavioral Therapy conference in Barcelona (2021), the International Convention of Psychological Science conference in Brussels (2022), the Association of Psychological Science conference in Washington, D.C. (2022), the Clinical and Health Psychology in Children and Adolescents conference in Valencia (2023), or the European Association of Clinical Psychology and Psychological Treatment conference in Amsterdam (2024). Moreover, the results have been presented in industry conferences such as the Society for Digital Mental Health. Finally, some results were presented in interviews for associations such as the Vereniging voor Gedrags- en Cognitieve therapieën (association of behavior- and cognitive therapies) in an attempt to bridge research and clinical practice.

Summary

This thesis explores the network approach to psychopathology as a novel alternative to the traditional medical model for understanding mental health disorders. The medical model views mental disorders as caused by underlying factors, often located in the brain, which lead to observable symptoms. However, this model has faced significant criticism due to its inability to explain the frequent overlap of symptoms across disorders, the issue of comorbidity, and the absence of consistent biological markers for many mental health conditions.

In contrast, the network approach suggests that mental disorders emerge from dynamic interactions between symptoms and other relevant variables, where the disorder itself is constituted by the relationships among symptoms rather than by an underlying cause. This perspective rejects the idea of static diagnoses, emphasizing the need for a more personalized and idiographic understanding of mental health. By focusing on how symptoms influence each other over time, the network approach provides a more flexible framework for assessing and treating mental disorders.

A key component of this thesis is the development of Ecological Momentary Assessment (EMA) tools, which enable the real-time capture of symptom fluctuations in daily life (Chapter 2). The presented tool was designed to assess psychopathology across various disorders (transdiagnostically), rather than being confined to single diagnoses. The thesis provides empirical evidence that using such EMA tool to assess a sample of university students was feasible, partially thanks to the overlap of traditional mental disorders categories (Chapter 3). Moreover, evidence that the specific questions of the EMA tool were related to baseline measures of psychopathology and varied enough tobe used in EMA studies is presented. However, potential adaptation to non-student samples might be necessary, and are discussed.

Another key component of this thesis investigates if there are differences in network structures and connectivity between individuals with differing levels of psychopathology (Chapter 4). The connectivity levels of people with differing levels of psychopathology were barely different and only a few connections differed. In conclusion, the network structures and connectivity of individuals with differing levels os psychopathology were not different. Possible explanations for these findings are discussed. Finally, the robustness of nomothetic network models, translatability from nomotehtic to idiographic network models, and heterogeneity of idiographic network models was investigated (Chapter 5). Nomothetic network models were robust, but the translatability from nomothetic to

idiographic network models was limited possibly due to the heterogeneity of idiographic network models.

The conclusions of this thesis advocate for shifting away from rigid diagnostic categories toward a more nuanced, individualized approach to treatment. This could help improving the effectiveness of mental health interventions by tailoring them to the unique symptom networks of each individual. This thesis thus positions the network approach as a promising and practical alternative to the medical model, one that better addresses the complexity and variability of mental health disorders.

Samenvatting

Deze thesis verkent de netwerkbenadering van psychopathologie als een nieuw alternatief voor het traditionele medische model voor het begrijpen van psychische stoornissen. Het medische model stelt dat psychische stoornissen worden veroorzaakt door onderliggende factoren, vaak in de hersenen, die leiden tot waarneembare symptomen. Dit model heeft echter veel kritiek gekregen vanwege zijn onvermogen om de frequente overlapping van symptomen tussen stoornissen te verklaren, het probleem van comorbiditeit en het ontbreken van consistente biologische markers voor veel psychische aandoeningen.

Daartegenover suggereert de netwerkbenadering dat psychische stoornissen voortkomen uit dynamische interacties tussen symptomen en andere relevante variabelen, waarbij de stoornis zelf wordt gevormd door de relaties tussen symptomen in plaats van door een onderliggende oorzaak. Dit perspectief verwerpt het idee van statische diagnoses en benadrukt de noodzaak van een meer gepersonaliseerde en idiografische benadering van geestelijke gezondheid. Door te focussen op hoe symptomen elkaar in de tijd beïnvloeden, biedt de netwerkbenadering een flexibeler kader voor het beoordelen en behandelen van psychische stoornissen.

Een belangrijk onderdeel van deze thesis is de ontwikkeling van Ecological Momentary Assessment (EMA) tools, die het mogelijk maken om symptoomfluctuaties in het dagelijks leven in real-time vast te leggen (Hoofdstuk 2). Het gepresenteerde instrument is ontworpen om psychopathologie transdiagnostisch te beoordelen, in plaats van zich te beperken tot afzonderlijke diagnoses. De thesis levert empirisch bewijs dat het gebruik van zo'n EMA-instrument om een steekproef van universiteitsstudenten te beoordelen haalbaar was, deels dankzij de overlap van traditionele categorieën van psychische stoornissen (Hoofdstuk 3). Bovendien wordt aangetoond dat de specifieke vragen van het EMA-instrument gerelateerd waren aan baseline-metingen van psychopathologie en voldoende variatie vertoonden om in EMA-studies te worden gebruikt. Mogelijke aanpassingen voor niet-studentenpopulaties worden besproken.

Een ander belangrijk onderdeel van deze thesis onderzoekt of er verschillen zijn in netwerkstructuren en connectiviteit tussen individuen met verschillende niveaus van psychopathologie (Hoofdstuk 4). De connectiviteitsniveaus van mensen met verschillende niveaus van psychopathologie verschilden nauwelijks, en slechts enkele verbindingen waren anders. Samenvattend waren de netwerkstructuren en connectiviteit van

individuen met verschillende niveaus van psychopathologie niet verschillend. Mogelijke verklaringen voor deze bevindingen worden besproken. Ten slotte werd de robuustheid van nomothetische netwerkmodellen, de vertaalbaarheid van nomothetische naar idiografische netwerkmodellen en de heterogeniteit van idiografische netwerkmodellen onderzocht (Hoofdstuk 5). Nomothetische netwerkmodellen bleken robuust te zijn, maar de vertaalbaarheid van nomothetische naar idiografische netwerkmodellen was beperkt, mogelijk vanwege de heterogeniteit van idiografische netwerkmodellen.

De conclusies van deze thesis pleiten voor het loslaten van starre diagnostische categorieën en het omarmen van een meer genuanceerde, individuele benadering van behandeling. Dit kan bijdragen aan het verbeteren van de effectiviteit van geestelijke gezondheidsinterventies door deze af te stemmen op de unieke symptoomnetwerken van elk individu. Deze thesis positioneert de netwerkbenadering daarmee als een veelbelovend en praktisch alternatief voor het medische model, dat beter recht doet aan de complexiteit en variabiliteit van psychische stoornissen.

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Curriculum vitae

Alberto Jover Martínez was born on May 1st 1994 in Valencia (Spain). In 2012 he graduated from secondary school (Bachillerato) from La Salle in Paterna (Spain). Afterwards, he completed a Bachelor degree (BSc) in Psychology from the University of Valencia (Universitat de València) in 2017. After that, from 2017 to 2019, he completed a Research Master in Cognitive and Clinical Neuroscience with a specialization in Psychopathology at Maastricht University (the Netherlands). During that time he completed an internship at the Interdisciplinary Center Psychopathology and Emotion Regulation (ICPE) of the University Medical Center Groningen (UMCG) in Groningen (the Netherlands). Between 2019 and 2023 he completed a Master abridged programme of Statistics and Data Science with a specialization in Quantitative Analysis in the Social Sciences at Katholieke Universiteit Leuven (Belgium). In 2020 he started a PhD position Eating Disorders and Obesity group of the Clinical Psychological Science departments ot the Faculty of Psychology and Neuroscience in Maastricht University under the supervision of Prof. Anne Roefs, Dr. Lotte Lemmens, and Dr. Eiko Fried. In October 2024 he started a master to become a psychotherapist in Spain.

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Submitted work

Jover Martínez, A., Lemmens, L. H. J. M., Fried, E. I., Haslbeck, J. M. B., & Roefs, A. (submitted). Does the structure of dynamic symptom networks depend on baseline psychopathology in students? *Behavior Research and Therapy*

Haslbeck J. M. B., Jover Martínez A., Roefs A., Fried E. I., Lemmens, L. H. J. M., Groot, E., & Edelsbrunner, P. A. (submitted). Comparing Likert and Visual Analogue Scales in Ecological Momentary Assessment. *Behavior Research Methods*

Jover Martínez, A., Lemmens, L. H. J. M., Fried, E. I., Waldorp L. J., & Roefs, A. (submitted). Robustness, generalizability, and heterogeneity of dynamic networks of psychopathology. *Multivariate Behavioral Research*

Conference presentations

11/21	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2021, November). Developing a psychopathology EMA questionnaire from scratch. A way to construct EMA questionnaires. ABCT 2021, 55th Annual convention of the Association for Behavioral and Cognitive Therapies (New Orleans, USA)
09/22	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2022, September). Transdiagnostic individual networks of psychopathology. EABCT 2022, 52nd Annual congress of the European Association for Behavioral and Cognitive Therapies (Barcelona, Spain)
03/23	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2023, March). Transdiagnostic individual networks of psychopathology. ICPS 2023, 4th International Convention of Psychological Science (Brussels, Belgium)
05/23	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2023, May). Validation of a transdiagnostic ecological momentary assessment measurement tool of psychopathology. APS 2023, 35th Annual Convention of the Association (Washington, D. C., USA)
06/23	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2023, March). Using mobile phones to illustrate the need for personalisation: a network approach to psychopathology. SDMH 2023, 2nd Annual Meeting of the Society for Digital Mental Health (Online)
11/23	Oral presentation: Jover Martínez, A., Lemmens, L. H., Fried, E. I., & Roefs, A. (2023, November). Are group-based models translatable to individuals? A network approach example with university students. Aitana 2023, 9th International Congress of Clinical and Health Psychology in Children and Adolescents (Valencia, Spain)
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