Mapping the relationship between stress, anxiety, depression and heart rate: an exploratory idiographic network analysis study

Kiran van Hall

December 2023

1 Abstract

Background: Despite decades of intense research effort, the etiology of mental illness remains obscured. The classic latent disease model fail to offer satisfying explanations to numerous questions regarding comorbidity or heterogeneity. In this paper we therefore employ a network approach to study psychological symptoms of stress, anxiety and depression on an individual level. We aim to integrate these symptoms into an idiographic network model with physiological indicators of stress and anxiety, to investigate the dynamics between physiological indicators and psychological symptoms, and explore person-specific dynamics.
Methods: Network analysis was performed using a graphical-VAR model to estimate the idiographic network of one participant (N=1). Psychological symptoms were assessed using the DASS-21 questionnaire, and heart rate (HR) and heart rate variability (HRV) using a wearable. Bridge centrality scores were computed and community detection was performed on all networks. Additionally, synchrony between the two symptom groups was assessed.
Results: The two symptom groups were synchronous in the absence of psychological distress. Network analysis showed that HR and HRV do not have a strong relation with stress or anxiety symptoms. However, HR did have high bridge strength centrality score.
Conclusion: HR and HRV did not show a strong relation to and were not predictive of stress and anxiety symptoms in the participant's idiographic network. Future work could focus on exploring the relationship between physiology and psychological symptoms in a cross-sectional network set-up to assess population level dynamics.

Keywords: Network analysis, Depression Anxiety Stress Scales, Wearables, Physiology, Idiographic science, EMA

2 Introduction

Mental disorders are one of the biggest contemporary health challenges, and significant portions of the developed world are presently experiencing a mental health crisis. The prevalence of mood and anxiety disorders has increased, while many countries are struggling with mental health care institutions that cannot meet the demand for help (Wainberg et al., 2017). Enhancing our comprehension of mental disorders is paramount for the advancement of more effective treatment and prevention methods. However, the root of many mental illnesses remains unclear, despite intense research efforts over the past decades within and outside academia. The number of publications of the topic has grown steadily since 2000, with a peak of 32555 articles containing mental health in the title or abstract in 2019 (Dimensions, 2018). Lack of progress can be explained by multiple factors, but an important one is diagnostic literalism (Fried, 2022). There seems to be a lack of diagnostic literalism among research psychologists . Researchers and clinicians understand mental disorders as groups of symptoms that are caused by an underlying disorder, also referred to as the latent disease model, which is illustrated in Figure 1 on the left. The latent disease model has driven contemporary research on mental health to find the underlying biological and cognitive essence of neatly separated diagnostic and statistical manual (DSM)-V mental disorders. However, this has proven to be challenging in the face of the multifaceted nature of mental illness (Fried, 2022). Diagnostic categories were never meant to be used as immutable truths to further build research hypotheses on top of. The categories were initially meant as a heuristic tool for clinicians, but were quickly institutionalized within the DSM and understood as indisputable (Whooley, 2014). For as long as the DSM has been around, there have been psychologists and psychiatrists criticizing it. Criticism ranges from the process of constructing it, the influence of the pharmaceutical industry to and an over-categorization of mental disorders (Hagan & Guilmette, 2015). This view of mental disorders as natural truths has in return led to reductionist research practices, that strive to find the one (biological) underlying cause of a mental illness. The cycle of diagnostic literalism and reductionism perpetuates a harmful loop of reification, evident whenever we discuss terms like "risk factors for bipolar type one disorder," "genes associated with autism spectrum disorder" or "symptoms indicative of post-traumatic stress disorder."

As an alternative to the stark categorization of DSM-V-based research, researchers have developed an alternative to the latent disease model to study psychopathology, namely a network analysis approach. Rather than assuming that a disorder is the underlying cause of symptomatology, the network approach to mental disorders posits that the complex interactions between symptoms actually give rise to a disorder (Borsboom & Cramer, 2013). Symptoms are represented by nodes in a network, and the statistical relations between symptoms are represented by edges and edge weights. The whole collection of nodes and edges together compiles the disease model. It views psychopathology as a complex dynamical system, the likes of which we also observed in other fields of study such as ecology, economy, or molecular biology (Barabási, 2012).

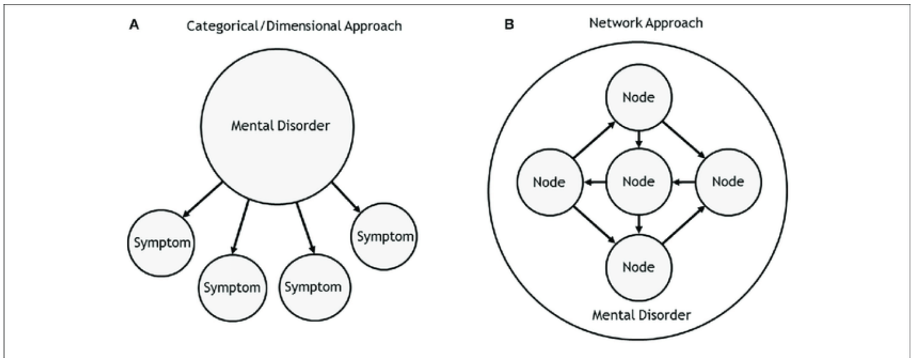

Figure 1: *The latent disease model (left) vs. a network model (right)* (Jones et al., 2017)

Interestingly, complex adaptive systems exhibit various universal characteristics that make it possible to draw on knowledge from other disciplines when studying psychopathology from a complex system point-of-view (Turner & Baker, 2019). Hence, by studying interactions between different symptoms within a complex network over time and applying what is already known from the field of complexity sciences, we can capture the complicated nature of mental disorders in a non-reductionist manner. It also opens the door for more idiographic research, which means the study of psychological phenomena on an individual level, contrary to nomothetic research, which studies these phenomena on a population level (Beltz et al., 2016). This is because constructing a psychological network does not rely on population averages, but can also be done by using only symptoms present in one individual by estimating statistical relations between symptoms on an intra-individual level. Therefore, network analysis is especially fit for idiographic psychology since the important part is how symptoms relate to one another, not how they are generalized among a population. The possibilities of modeling patient-specific symptom dynamics are promising new approaches within the field of psychopathology that solve the problem of reductionism and categorization altogether. Moreover, viewing mental illness as a complex adaptive system that can be studied idiographically has far-reaching consequences on how these models can be applied in clinical settings (Burger et al., 2020; David et al., 2018).

This view of psychopathology as an interplay between multiple systems within an individual is also supported by another model, namely he biopsychosocial model. This model understands psychological disorders as an interplay between three systems. The biological system, consisting of genes, brain functionality and physiology, the psychological system, encompassing thoughts and behaviours and the social system, namely family and friend relationships and socio-economic factors (Kusnanto et al., 2018). Within the paradigm of network analysis, there has been vasts amount of research on the dynamics between different psychological and social factors, but biological factors remain outside of the research scope. While there has been research on the adaption of neuroimaging data into psychological networks (integrating functional magnetic resonance imaging (fMRI)) (Bathelt et al., 2022), little work has been done to inclide a broader suite of physiological information into psychological networks. This could potentially be very interesting for clinical and research practice, seeing the low cost and minimal invasiveness by which physiological data can be gathered nowadays. The utilization of digital resources is crucial in this endeavor, as there is a shortage of healthcare personnel and the automation of data collection outside of clinical settings is becoming increasingly significant in the context of monitoring and preventing mental health disorders. Therefore, in this paper, we will investigate the relationship between affective and physiological symptoms using a network analysis approach.

2.1 Current Study

The current study aims to explore the integration of physiological markers into an idiographic network model of low mood and stress. This will be done by estimating the network using time-series data gathered over a longer period of time from a single participant. During this period, mood will be assessed through the use of questionnaires and physiological data will be gathered simultaneously using a smart watch. The remainder of this paper is structured as follows. First, we provide a literature review in the background section. Then, we continue to describe the experimental setup in material and methods, after which we will give a detailed report of our findings in results. Lastly, we'll discuss the results and reflect on the experiment in the discussion.

3 Background

As already touched upon in the introduction, the current disease model of mental illness falls short on several fronts. Disease categories are arbitrary and often shaped by history as opposed to empirical evidence. Research has focused mostly on studying these different disease labels by comparing a healthy population to a diagnosed one, instead of studying underlying biopsychosocial processes that may give rise to disease (Fried, 2022). One of the most notable examples is the serotonin theory of depression, which states that depression is caused by lower levels of the neurotransmitter serotonin. This theory has inspired the development and use of selective serotonin reuptake inhibitors (SSRIs), but systematic reviews on the serotonin theory point to inconclusive results (Moncrieff et al., 2022).

Another issue with the latent disease model is that it does not account for high comorbidity in patients. 45% of patients suffering from one mental illness also are diagnosed with one or more other ones (Cramer et al., 2010). If different categories of mental disorders are truly caused by different underlying factors, these high rates of comorbidity would be unlikely. Furthermore, there is a significant amount of heterogeneity (Allsopp et al., 2019) and time variance (Caspi et al., 2020) within DSM-V diagnostic categories, indicating a more complicated and individual-specific nature of psychopathology. DSM categories are based on a nomothetic way of studying disorders, meaning that we understand them in terms of inter-individual variation. The drawback of this is that research and treatment will be based on these averages, while they often don't apply to individual patients due to the high variability in which mental disorders tend to present. It also builds further on and reinforces the stark boundaries imposed between disorders by the latent disease model, while it is clear that a significant number of patients do not even fit into one category. In conclusion, even if the in some parts of psychology the scientific consensus over the past years seems to have been moving towards a more idiographic view of mental illness, other parts of psychological research and, most importantly, clinical practice, still rely heavily on nomothetic research methods and treatments (Molenaar, 2004). However, what if we did not describe mental disorders as general deviations from big population averages, but would focus more on dynamics within individual patients? This approach could lead to more person tailored health care and more effective treatment (Molenaar & Valsiner, 2018).

3.1 Idiographic network models

Idiographic network modeling is a relatively new development in the field of network psychometrics and presents an alternative to the nomothetic research paradigm currently reigning in psychology. Idiographic network models can be used to study how symptoms change their dynamics within an individual over time and tease out network features and dynamics that are unique to one patient by studying intra-individual variation (Burger et al., 2020; Molenaar & Valsiner, 2018; Epskamp et al., 2018b). These symptoms can be divided into three categories: cognitive, psychological, and physiological . Psychological symptoms can include low self-esteem, low mood, rumination, and hopelessness. Cognitive symptoms include the ability to concentrate, being indecisive, and learning and memory problems (Perini et al., 2019). Physiological indicators of mental illness can be low physical activity, disturbed sleep, low appetite, and elevated heart rate (HR). The majority of current research in network analysis has focused on cognitive and psychological symptoms, but biological symptoms could also be interesting to have a complete and holistic biopsychosocial perspective of a patient. Idiographic network modelling can also be tailored to specific types of patients, like patients suffering from mood and anxiety disorders (Fisher et al., 2017), and are constructed using environmental momentary assessment (EMA) or experience sampling (ESM) data. Moreover, it can also be used to make predictions about disease progression in patients, and possibly detect early warning signals (EWS) that may point to sudden gain or losses in patient well-being (Olthof et al., 2023; Wichers & Groot, 2016). In complex dynamical system sciences, systems can have states. However, the system can get out of balance due to factors from outside and inside. The network becomes unstable until it finds a new equilibrium. When a network becomes unstable, it exhibits particular characteristics that indicate that the system is moving to a new equilibrium, namely critical slowing down and critical fluctuations (Wichers & Groot, 2016; Olthof et al., 2023). These are observable before the system settles in its new state, potentially a psychopathological state, and can therefore potentially be used as an EWS to intervene before the system settles in a pathological state.

3.1.1 Preliminaries Network Analysis

Network consist of *nodes* and *edges*, in which nodes represent distinct elements of a system, and edges the connection between these elements. In psychometric network models, nodes represent symptoms, and edges the association between symptoms. Edges can be *directed*, representing a specific direction between nodes, and *weighted*, indicating the strength of the connection. Moreover, edges in psychometric network are often *signed*, meaning they are either positive or negative, indicating the nature of the relationship between nodes. Node centrality statistics are commonly used measurements in network analysis and graph theory, ranking nodes based on their network position. Three commonly used centrality measures are strength, closeness and betweenness. *Strength centrality* is the total sum of all the edge weights absolute values and is a measure of the node's overall connectedness. *Betweenness centrality* measures how crucial a node is in the connectedness of the whole network by measuring how many shortest paths a node is a part of. These nodes act a bridges in the overall network. *Closeness centrality* is a measure of how close a node is an average to all the other nodes in the network. In the context of psychometric networks, these centrality measures can be interpreted in terms of symptom's role in pathology. In this paper we will be employing a variation on these centrality measures, namely bridge centrality scores. Strength, closeness and betweenness are still defined the same as in normal centrality scores, but instead of looking at all nodes, bridge centrality scores only consider nodes from different communities (Jones et al., 2019). This has the advantage of clearly quantifying what nodes are connecting different communities rather than separate individual nodes. *Communities* in network analysis refer to a subset of nodes within a network that are more densely connected among each other than the rest of the network (Radicchi et al., 2004).

3.2 Physiological Markers in Mental Health Care

The inclusion of physiological data in mental health research and assessment may be crucial. Earlier research has shown that tracking changes in activity and movement could be used as a key indicator in changes in mood stages since low physical activity could be indicative of an oncoming depressive episode (Patel & Saunders, 2018). Moreover, physical activity measured by smartphone accelerometers has shown that there is a strong correlation between activity manic or depressive phases in patients with bipolar disorder (Grünerbl et al., 2015). Lastly, passive sensing data on containing patient activity from smartphones has been used in combination with EMA data to predict relapse in chronic schizophrenic patients (Adler et al., 2020). Another factor that is highly relevant to psychopathology is stress. Two common physiological markers for stress in people are HR and heart rate variability (HRV). A study by Dalmeida & Masala (2021) developed a web application measuring HRV to predict stress levels. After analysis of the Apple Watch data, it predicted stress states with 71% probability and relaxation states with 79% probability (Dalmeida & Masala, 2021). Another validation study by Hernando *et al.* (2018) investigated the impacts of various HRV statistical models in both time and frequency domains, in both relaxed and stressed states, and compared the various statistical methods for their accuracy (Hernando et al., 2018). A literature review by Lui *et al.* (2022) identified multiple physiological variables that can be assessed with an Apple watch that are relevant for mental health research (Lui et al., 2022). HR and HRV were assessed rather accurately according to their review of 19 papers using the Apple watch. HR and HRV are indicative of sympathetic nervous system activation and are the most useful to assess panic attacks and anxiety disorders since those disorders are characterized by over-activation of the sympathetic nervous system. Moreover, studies investigating the psychological implications of the disparity between the sympathetic and parasympathetic nervous systems found that HRV may be a superior physiological indicator of stress compared to HR. An uneven ratio between these two components indicates a higher prevalence of stressful stimuli (Dalmeida & Masala, 2021). Low physical activity on the other hand is associated with depression and lethargy. HRV can be calculated in several ways, and the Apple Watch employs the SDNN calculation, which is the standard deviation of the 'normal heart beat' interval, meaning ectopic beats are removed from analysis (Shaffer & Ginsberg, 2017).

3.3 Recurrence Quantification Analysis

However, no single feature or measurement is completely transparent to anxiety or depressive states, so a multidimensional approach is more fitting when investigating the coupling between physiology and emotional states and dynamics. To research the dynamics of these two systems better, we propose the employment of recurrent quantification analysis (RQA). RQA stems originally from physics and chaos theory but is now widely used in other sciences, like physiology and social sciences. However, the application to biopsychological processes is however fairly new. The most important part to note about an RQA is that it measures recurrence or repetition (Wallot & Leonardi, 2018). It compares a time series and analyses how often a certain system state reoccurs within that time series. The system's possible states are mapped in its phase space. When comparing two or more time series, it is called crossed recurrence quantification analysis (CRQA) and it compares how often system states co-occur or precede or follow each other in phase space. The latter will be employed for the analysis of the physiological and psychological data. We opted for the use of CRQA to gain insight of the synchronisation between the two systems. It is a effective way to quantify synchronisation, and even though it does not tell us anything about dynamics between symptoms, it will be informative to see if the two systems on a macro-scale have a relation or not.

In conclusion, there has been extensive research on the relationship between physiological markers, EMA and ESM data, and mental health issues. However, very little research has been done to integrate the physiological component of mental health problems into the network model. There has been research on the relationship between physiological and cognitive symptoms in mental health, and it shows that physiological symptoms can be important indicators of mental health issues. They have the upside over cognitive/emotional symptoms in that they are objective quantifiable, and could therefore serve as an important marker. They are also preferable over more invasive and expensive methods such as fMRI. It is therefore important to incorporate these factors into research on mental health using network analysis and RQA since they provide additional context. They can also be helpful to gauge the level of distress a patient is going through when a patient themselves is unable to indicate this properly (Lui et al., 2022). However, it is important to note that while physiological markers may serve as an indicator for mental health problems, conclusions about a patient's well-being can only be drawn when also the mental state of the patient is assessed.

3.4 Expectations

We expect that the stress and anxiety items will have strong connections with the HR and HRV measurements within the network since previous literature established that high arousal associated with stress and anxiety can be found in HR and HRV (Lui et al., 2022). Therefore, we also expect to observe the presence of synchrony between the psychological system and physiological system. Furthermore, we expect that intra-individual dynamics of the network remain largely the same in across networks with and without physiological data. Moreover, it is expected that the three subdomains of the DASS-21 form three communities within the network if all measures indeed measure the same subdomains, which was found in earlier network analysis studies (Van den Bergh et al., 2021). Lastly, we expect HR and HRV to have high bridge centrality scores, since high HR and high HRV are associated with both stress and anxiety.

4 Material & Methods

4.1 Participant

The participant is a 27-year-old male. He was recruited face-to-face from the researcher's social network. The participant was informed by means of an information sheet and a face to face discussion before the experiment commenced, and written informed consent was obtained beforehand. After the experiment was concluded, the participant was debriefed. Debriefing also took place face to face, and contact details of the researchers were provided. We refer the reader to the appendix for a more in depth look of the information sheet that was used. This study was approved by the ethics committee of the University of Leiden.

4.2 Measurements

4.2.1 Physiological Measures

For collecting physiological data we used an Apple Watch Series 7. Data was exported in XLM format and parsed into separate CSV files in Python (Version 3.11) using a pre-written data parser from GitHub for Apple Watch data (njr0 et al., 2021). Then, the data was parsed again to separate date and time into columns using a supplementary data parser (Meyer, 2021). Irrelevant data (device type, device name, source name, and unit) were removed to simplify analysis. Moreover, data from outside of the time scope of the experiment was also destroyed before analysis.

4.2.2 EMA Measurements

To assess levels of stress and low mood in participants, we used the Depression Anxiety Stress Scale-21 (DASS-21) questionnaire, a shortened version of the DASS-42. This questionnaire was designed to quickly identify different domains of stress anxiety and depression in both clinical and non-clinical populations, and is not a diagnostic tool (Makara-Studzińska et al., 2022; Osman et al., 2012). The depression scale assesses dysphoria, hopelessness, devaluation of life, self-deprecation, lack of interest, anhedonia and inertia. The anxiety scale assesses autonomic arousal, skeletal muscle effects, situational anxiety, and subjective experience of anxious affect. The stress scale is sensitive to levels of chronic non-specific arousal, such as difficulty relaxing, nervous arousal, and being easily agitated, irritable and/or over-reactive and impatient. Separate depression, anxiety and stress scores are calculated by adding all the scores for the relevant items of each domain, and the total score is then calculated by adding these three together.

Previous longitudinal research has used the DASS-21 to assess stress, anxiety, and low mood in combination with physiological data to investigate statistical relations between the two, and found a strong correlational relationship (Knight & Bidargaddi, 2018). Additionally, it has also been used in research to estimate the global psychopathological network model of anxiety, stress, and depression and found that different nodes of the three dimensions cluster together, and form communities (Van den Bergh et al., 2021). Given these two preliminaries, we found the DASS-21 a fitting tool for the current paper to assess stress, anxiety and depression. Although the DASS-42 provides more data points, we decided on the DASS-21 to not overburden the participant. Moreover, the presence of duplicate items in the DASS-42 could influence the network structure (Van den Bergh et al., 2021). The two questionnaires still cover the same 3 domains, but the DASS-42 has 14 items per domain and the DASS-21 has 7 items per domain because of the elimination of duplicates (Makara-Studzińska et al., 2022). Importantly, the DASS-21 is robust in all 3 domains (Osman et al., 2012). Exactly how items of the questionnaire relate to each of the three domains can bee seen in Figure 2. For the whole questionnaire, we refer the reader to the Appendix.

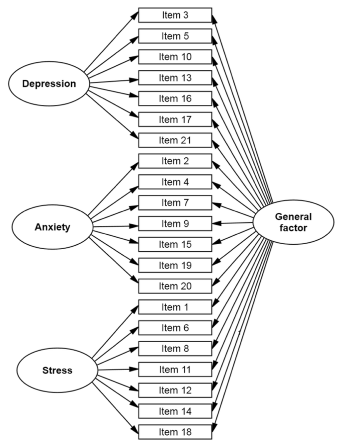

Figure 2: *A schematic representation of the three domains of the DASS-21 and their corresponding items* (Lee & Kim, 2022)

4.3 Experimental set-up

The experiment took place over the span of 15 days. The DASS-21 was constructed in Qualtrics and could be filled in by the participant on either their smartphone or laptop via a link provided to them (Qualtrics Development Company, 2005). The questionnaire was filled in bi-daily, once in the morning around 10 am and once in the evening, around 10 pm. Physiological data was recorded during the day, from waking until bedtime.

4.4 Network and Recurrence Quantification Analysis

4.4.1 Network estimation

The networks were estimated using the graphical-VAR (Version 0.3.3) package for R (Version 3.1.0) developed by Epskamp (2018), aimed at network analysis for $n = 1$ networks, or idiographic networks. Graphical-VAR uses penalized maximum likelihood estimation to estimate model parameters (edge weights) while simultaneously controlling for edges that are removed due to the sparse network estimation. Bayesian information criterion (BIC) model selection was applied to select the best-fitting model out of 2,500 different models for the graphical-VAR package estimates (Epskamp et al., 2018a). The function returns a partial contemporaneous correlation (PCC) network and the partial directed correlation (PDC), or temporal network. Temporal networks show the predictive relationship of one variable for another variable in the next time window, and can also be computed for the same variable autoregressively. Contemporaneous networks on the on other hand show the predictive relationships between variables in the window of measurement, which could indicate a causal relationship (Epskamp et al., 2018a). Bridge centrality measures were estimated using the network-tools (Version 1.5.1) package for R, which calculates betweenness, closeness, and node centrality measures for non-specific networks and plots these measures (Jones et al., 2019, 2018). It also employs the spinglass algorithm for community detection, which was also used in the current study.

CRQA was conducted using the CRQA package (Version 2.0.5) for R (Coco & Dale, 2014). Using these packages cross recurrence plots (CRP) were created, which are a way to visualize the recurring states in the phase space of a dynamical system using a matrix. This means that the re-occurrence of a state between one or multiple systems is plotted over time (Marwan & Kraemer, 2023). To calculate recurrence, a threshold is needed to decide when the system is classified as being in a recurrent state or not. The threshold essentially sets how different two states can be to be classified as the same, or recurrent. For the categorical data obtained from the questionnaire, no threshold is set because states either match or do not match. It is not possible to let the threshold empty in the function, so we made it insignificantly small, as recommended by Wallot (2018), which gives us $\varepsilon = D_{0.000001}$. Additionally, instructions for parameter settings for raw categorical data were followed, with an embedding of $m = 1$ and a delay of $d = 1$, and datatype was set to categorical (Wallot & Leonardi, 2018).

4.4.2 Data Conversion

To effectively compare the DASS-21 outcomes and the HR and HRV, we converted the continuous physiological data to discrete data. We created 4 categories, 0, 1, 2, and 3, so it would correspond with the DASS-21. The continuous data then needed to be re-categorised to fit in these for categories. We did this by first calculating the average resting HR and the average HRV to construct category o. Then we constructed the categories 1, 2, 3 by adding 1, 1.5 and 2 standard deviations to these means. The threshold for each category can be seen in Table 1. Resting HR was chosen as category 0, since 0 in the DASS-21 indicates rest, or the absence of any psychological symptoms, which should make the comparison between the two categories work. Moreover, we purposefully did not use the average HR, since there are some significant outliers in the HR data, and we think that therefore the average resting HR is a better reflection of a relaxed, stress/anxiety absent state than the average HR.

Table 1: Threshold conversion values for each category of physiological data

Measurement	0	1	2	3
HR	≤ 88	≤ 95	≤ 103	> 103
HRV	≤ 35	≤ 55	≤ 78	> 78

We perform a window analysis on the physiological data, which means we will calculate the average over multiple data points in a time frame. Window size was determined by looking a the raw data plot, and see how broad maxima and minima are, so size can be chosen in a way that captures average of a window without missing any local maxima or minima. Window size for the analysis was set on the size of an hour.

5 Results

5.1 Exploratory Analysis

First, we did an overall statistical analysis of all the collected data, namely the HR, HRV and DASS-21 scores. Results can be seen in Table 2, which shows average HR, average HRV and DASS-21 scores, with their medians and standard deviations. Looking at Table 2, it is interesting to see the standard deviation for the DASS-21 scores is quite high, 13.34 on a questionnaire with a maximum score of 63, indicating a high variance. This can be further explained when looking at Figure 3, which shows the total score of each of the three domains per assessment, and the total DASS-21 score which is all three domains added together. Three major peaks can be observed in all domains simultaneously, with the biggest one halfway through the experiment. Interestingly, when looking at Figure 3, the different dimensions all peak at the same time, and overall peaks in the total score seem to be the result of an increase in all domains, and not just one. This indicates that the three domains may not be independent from one another.

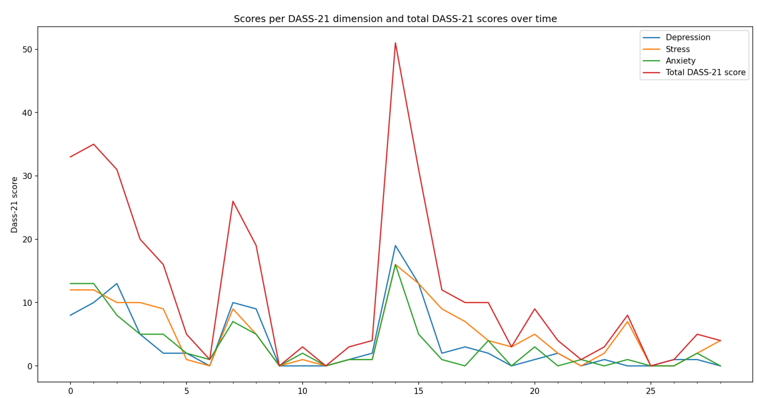

Figure 3: Total DASS-21 scores, and additionally each dimension plotted separately. The X-axis is the measurement number, the Y-axis is the DASS-21 score corresponding to that measurement

5.2 CRQA

Secondly, we performed CRQA analysis to investigate whether the overall system states of the psychological system and physiological system were synchronous, and when this was the case. CRQA analysis between the HR and DASS-21 scores showed a recurrence rate (RR) of 11.6% and between HRV and DASS-21

Table 2: Descriptives Physiological Data and DASS-21

Measurement	N	Mean	Median	SD
HR	5495	102.2	100.0	16.1
HRV	93	38.05	35.00	17.62
DASS-21	29	12	5	13.34

a RR of 9.8%. In Figure 4, the CRPs of the CRQA analysis between the psychological system and HR and HRV systems are shown. In both plots it can be observed that synchrony is present, namely between measuring point 7 an 14 and 21 and 27. When looking at Figure 3, it is notable that these to intervals are clearly around the same time as the absence of peaks in the DASS-21 scores, and the absence of recurrence between the two systems during the peaks in questionnaire scores.

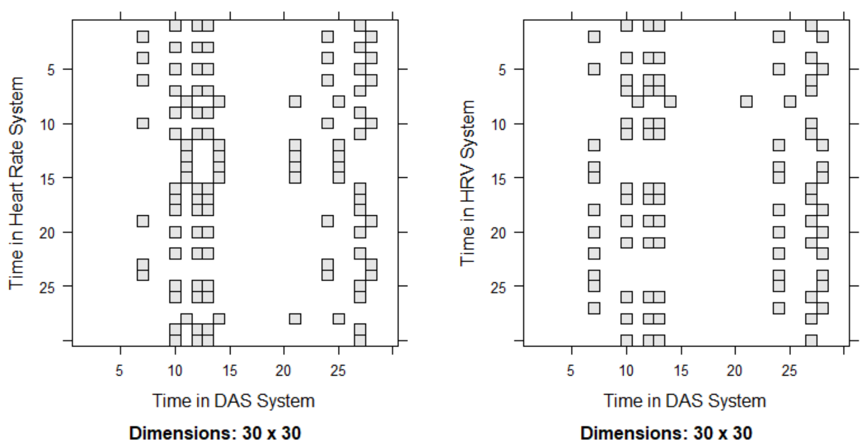

Figure 4: CPRs of HR and DASS-21 scores (right) and HRV and DASS-21 scores (left). The x-axis shows the time in the DAS system and the y-axis shows time in the HRV system, with each point representing a measuring point. Squares indicat the presence of recurrence between the two systems.

5.3 Stress, Anxiety and Depression Network

We then performed a network analysis of the DASS-21 scores separately. Figure 5 shows the participant's contemporaneous network and temporal network of anxiety, stress and depression symptoms over the time window of 15 days. First, we will have a closer look of the person-specific dynamics of the contemporaneous and temporal networks. In the contemporaneous network, we see that nodes Q21 (*"I felt that life was meaningless"*) has strong connections with node Q17 (*"I felt I wasn't worth much as a person"*) and Q15 (*"I felt I was close to panic"*). Additionally, Q20 (*"I felt scared without a good reason"*) which mediates a relationship between Q10 (*"I felt like I had nothing to look forward to"*) and Q9 (*"I was worried about situations in which I might panic and make a fool of myself "*). Moreover, we see a triangle connection between Q1 (*"I found it hard to wind down"*), Q12 (*"I found it difficult to relax"*) and Q8(*"I felt that I was rather touchy"*). In the temporal network, item Q2 (*"I was aware of dryness of my mouth"*) has the most inwards and outwards edges, plus a self-directed edge. Q18 (*"I was rather touchy"*) has an outward edge to both Q2 and Q14 (*"I was intolerant of anything that kept me from getting on with what I was doing"*), which also share and edge. These three nodes make up a very apparent triangle in the temporal network. Q15 (*"I was close to a panic"*) has a directed edge to Q2, and Q2 has a directed edge to Q7 (*"hands trembling"*).

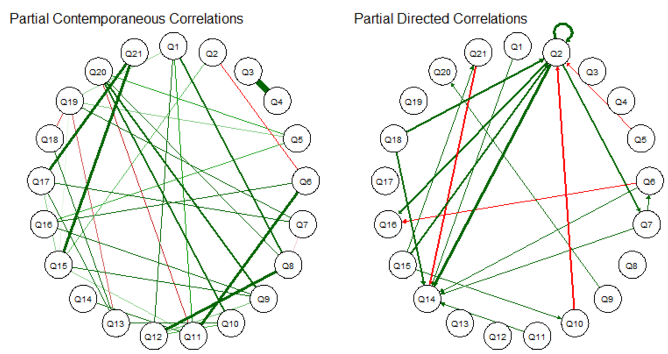

Figure 5: Contemporaneous Network (right) and Partial Temporal Network (left). Green represent a positive edge sign and red a negative edge sign. Edge thickness represents the edge weight. The number indicates to which item of the questionnaire the node corresponds.

Then, we estimated centrality measures of the contemporaneous network and performed community detection using the spinglass algorithm. Figure 6 shows three different centrality scores for each node, namely bridge betweenness, bridge closeness, and bridge strength) Q13 (*"I felt down-hearted and blue"*)shows high bridge centrality scores for all three different measures (*bridge betweenness = 47, bridge closeness = 0.11, bridge strength = 0.7*). Q11 (*"I found myself getting agitated"*), also had a high bridge centrality score across different measures (*bridge betweenness = 25, bride closeness = 0.08, strength = 0.7*). Q15((*"I was close to a panic"*) had a high betweenness and closeness centrality (*bridge closeness = 0.08, bridge betweenness = 39*). Figure 6 also shows different communities, each node color representing a community. It shows the presence of three different communities, which can also be seen in Table 3. Interestingly, the communities found in the analysis do not correspond with the 3 dimensions as seen in Figure 2.

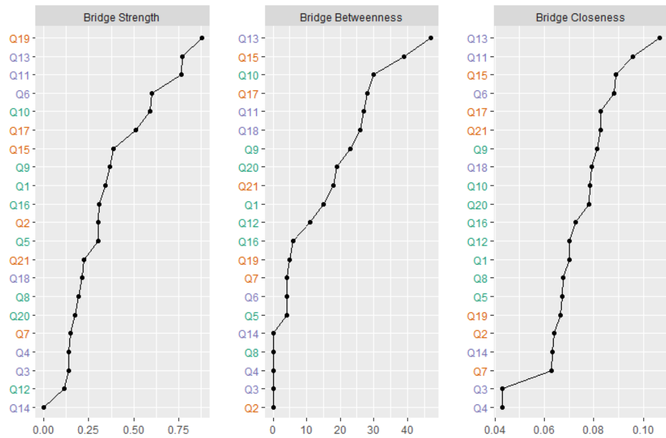

Figure 6: Centrality measures bridge strength (left), bridge betweenness (middle) and bridge closeness (right). Y-axis shows nodes, x-axis centrality scores. Colors indicate node membership (Jones et al., 2019)

Table 3: Communities PCC network

Community 1	Community 2	Community 3
Q1	Q2	Q3
Q5	Q7	Q4
Q8	Q15	Q6
Q9	Q17	Q11
Q10	Q19	Q13
Q12	Q21	Q14
Q16	.	Q18
Q20	.	.

5.4 Physiological Network

We then estimated the network including the HR and HRV, by combining the DASS-21 scores data frame with the data frame containing the HR and HRV scores and using this as input for our graphical-VAR estimator. The resulting contemporaneous network and temporal networks can be seen in Figure 7. The contemporaneous network shows again the mediation between node Q21 (*"I felt that life was meaningless"*), node Q15 (*"I felt I was close to panic"*) en Q17 (*"I felt I wasn't worth much as a person"*). This structure is the same as seen in the

DASS-21 network. Additionally the same can be observed for Q20 (*"I felt scared without a good reason"*) which mediates a relationship between Q10 (*"I felt like I had nothing to look forward to"*) and Q9 (*"I was worried about situations in which I might panic and make a fool of myself "*), which was also present in the DASS-21 network. Lastly, we see the same triangle connection between Q1 (*"I found it hard to wind down"*), Q12 (*"I found it difficult to relax"*) and Q8(*"I felt that I was rather touchy"*) as in the other condition. Interestingly, HRV had a strong negative edge with Q6 (*"I tended to overreact"*), and HR a strong negative edge with Q19 (*"I was aware of the action of my heart in the absence of physical exertion"*). The temporal network shows the same triangle we previously observed between node Q2, Q18 and Q14. Also, the same strong edge from Q2 to Q7 (*"hands trembling"*) was present. HR and HRV had no strong edges in the temporal network.

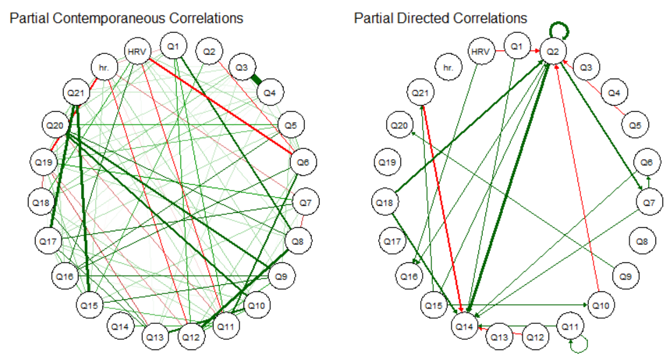

Figure 7: Contemporaneous network (right) and the temporal network (left). Green edges represent a positive edge sign and red edges a negative edge sign. Edge thickness represents edge weight. The number indicates to which item of the questionnaire the node corresponds and HR and HRV

Figure 8 shows the bridge centrality scores of the network, some of which remained consistent were consistent across networks and some not. Analysis shows that HR had a high bridge strength centrality (*bridge strength = 0.88*) in the network, and this was also true for HRV (*bridge strength = 0.55*) to a lesser degree. Interestingly, both HR and HRV measures also had low bridge betweenness and closeness centrality scores. The high bridge strength centrality of Q19 (*bridge strength = 1.11*) remained the same compared to the DASS-21 network, but Q13 and Q15 has notably a less high closeness centrality score of *0.8*, while consistently having high bridge betweenness centrality scores of *38* and *51* respectively. Community detection was also performed, and showed that HR and HRV are part of the same community, among other nodes which can be seen in Table 4. Community two remained the same compared to the DASS-21 network, but community one and three changed, with nodes Q5, Q6, Q10, Q11, Q14, Q16 Q20 changing community membership and community three gaining nodes, both questionnaire items and HR and HRV.

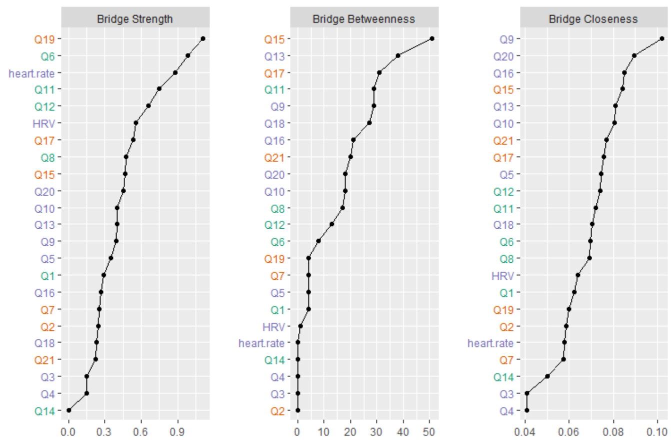

Figure 8: Centrality measures bridge strength (left), bridge betweenness (middle) and bridge closeness (right). Y-axis shows nodes, x-axis centrality scores. Colors indicate node membership (Jones et al., 2019)

Table 4: Communities Contemporaneous Network

Community 1	Community 2	Community 3
Q1	Q2	Q3
Q6	Q7	Q4
Q8	Q15	Q5
Q11	Q17	Q9
Q12	Q19	Q13
Q14	Q21	Q16
.	.	Q18
.	.	Q20
.	.	HR
.	.	HRV

6 Discussion

The current study investigated the relationship between physiology en psychological state through the means of network analysis and CRQA. Most notable findings include that high HR and high HRV do not predict stress items or anxiety symptoms in the same time window and the absence of synchrony between the two systems in the presence of psychological distress. Moreover, temporal network analysis showed that high HR and HRV did not predict stress or anxiety symptoms in the time window after. CRQA analysis pointed towards synchronisation between physiological system and psychological system in the absence of stress, depression or anxiety. Synchrony was however absent in the periods of high scores. Notably, important personal dynamics were consistent across the two kinds of networks. These included a strong triad in the temporal network between being touchy, being intolerant and having a dry mouth, showing that being touchy is often a starting symptom that results in being intolerant and experience the physical symptom of having a dry mouth. This makes sense from a theoretical point of view, since two out of three symptoms assess a core symptom of anxiety, namely being easily agitated, with a physical component of overall arousal. Other relationships found included dry mouth predicting trembling of hands in the next time window. This is in line with expectations, since both are well-known physical indicators of stress and anxiety. Moreover, we saw in the contemporaneous network a relationship between panic and worthlessness mediated by a sense of meaninglessness. We also saw a relationship between being scared, nothing to look forward to and a fear to embarrass oneself. Both of these unclosed triangles consist of a mix between anxiety and depression symptoms. While for example panic, worthlessness and meaninglessness do not belong to the same category of symptoms, co-occurrence of depressive and anxiety symptoms is very common, since the two disorders are highly co-morbid (Kalin, 2020). We also found a triangle consisting of three different stress symptoms that was consistent across conditions. Another notable finding was the negative relation between a high HR and the awareness of one's own heart beat. This negative relation indicates that awareness of heart beat may not be caused by a high HR, and could be more a perceptual matter. A study found that generalised anxiety disorder (GAD) did interfere with processing of interoceptive signals, which could offer an explanation to this finding (Pang et al., 2019). This was also confirmed by the participant during debriefing, where he mentioned that whenever he was aware of his heart beat he checked the Apple watch, but found the HR was normal. Another contributing factor may be that the self-report like the DASS-21 questionnaire may not be as suited to the assessment of physiological symptoms as to cognitive ones (Van den Bergh et al., 2021). This could also explain the lack of connection between perception of HR and actual HR in the network. Furthermore, it was also observed that the three domains of stress, anxiety and depression showed increases and decreases at the same time. This is in line with previous literature on the DASS questionnaire, stating that the three domains are moderately inter-correlated, due to common causes such as (negative) environmental events affecting all domains somewhat (DAS, nd).

It is also important to consider that the questionnaire used in the current study was designed to assess symptoms over the span of a week, while it was used to assess symptoms over the span of several hours. While it is possible to use a different time frame according to the official DASS manual, it may not be as comparable to other studies that did employ a week long time frame (DAS, nd). The participant also mentioned that the past tense phrasing of the questionnaire was confusing at times, and that the time period over which he has to consider his symptoms was somewhat unclear. This could have influenced the results of the questionnaire scores, and should be adjusted in future studies by making it very explicit what time window the questionnaire is referring to. As mentioned earlier, HR and HRV also had low connectivity in the temporal network, which can be explained by the fact that high HR and HRV may indicate acute stress and therefore co-occurs with stress and anxiety symptoms, but does not precede these states if they also fade away quickly.

Interestingly, both HR and HRV measures also had low bridge and closeness centrality scores, meaning they did not connect two communities of symptoms often, and were not close to nodes from other symptom communities. Analysis did show that HR had a high bridge strength in the network, and thus was connected to a high number of other symptoms in the same time window from different clusters. However, this could be the result of many small edges, since HR has very few edges with a high edge weight. Therefore, given the lack of large edges and absence of other high bridge centrality scores, it remains unclear whether this bridge strength score indicates that a high HR acts as a bridge between different symptom clusters, or is just an artefact of many small edges the node has.

Results from the community detection showed that there are three communities of nodes present, which is in line with previous findings. Node membership differed however, and items from the DASS-21 that measure the same dimension did not always belong to the same community, which is not in line with the findings of van den Bergh, Marchetti & Koster (2021), which found that items measuring the same dimension did belong to the same communities. There could be multiple explanations for this. Most importantly, van den Bergh, Marchetti & Koster (2021) focused on cross-sectional networks constructed using data from a vast open science database, and the current study focuses on idiographic networks. Therefore, it could be that on a population level these nodes do form communities around the same dimensions they measure, but that in individuals this differs, due to person-specific symptom interactions. We also found that communities were not the same across conditions. This can be explained by the fact that adding nodes and with many (small) edges changes how the algorithm parses the graph into communities.

One of the more notable limitations of the current study is the conversion of continuous data to categorical data, which leads to an inadvertent loss of information. We tried to minimize information loss by first establishing the window size according to the width of peaks in the continuous data, so no minima or maxima were missed or cancelled out by each other. However, loss of information cannot be completely prevented using this method, which could have influenced results by obscuring relations that may have been present in the original data. Another limitation is the n=1 design of the study, since it could be that the lack of relation between HR and anxiety and stress symptoms is person specific. However, it is also important to note that the goal of this study was to gain insight in person-specific symptom dynamics, and the absence of a relation between HR and HRV and psychological stress could also be a valid finding for any treating physician. The sampling frequency of twice a day may also not have been sufficiently high, which could have lead to missing of dynamics in the psychological domain and a higher sampling frequency would have allowed for a more accurate capture of these dynamics. Another paper on personalised network models mentioned that high frequency measuring of ESM data over a short period of time is a strategy that can be employed effectively for the estimation of personalised networks (Epskamp et al., 2018a). It would be interesting to repeat the current study with a higher sample rate to see if there are any dynamics that were not captured using a bi-daily sample rate. This could also help minimize information loss within the physiological domain.

The current study explored the possibilities of integrating physiological data into psychometric network analysis to and laid bare some technical and experimental hurdles for future application. Idiographic network modelling is fairly new within the field of psychology, and further research into idiographic network modelling and physiological markers integration can prove to be important for future developments of patient care and assessment. The current study also illustrated using the idiographic approach how much an individual person can differ from the population average regarding symptoms of anxiety, stress and depression, and raises questions on how crucial it may be to consider these differences in a clinical setting. Further development could aid in providing an accurate out-clinic and personalised alternative and/or supplement to in-person clinic interviews to decrease workload for mental health care professionals and provide patient specific insights to increase treatment effectiveness (Burger et al., 2020). Future research could focus on developing techniques to integrate the continuous physiological data with questionnaire data to prevent loss of information. Population-level network structures could also be estimated using a cross-sectional approach with big sample sizes, to test relations of physiological markers with psychological symptoms on a population level. Moreover, further exploration of other wearable data in the use of network analysis could be done, for example energy expenditure, which has shown to have strong relations with depressive and manic states in bipolar patients.

References

(n.d.). Depression anxiety stress scales (dass) - frequently asked questions. https://www2.psy.unsw.edu.au/dass/DASSFAQ.htm. Accessed: January 11, 2024.

Adler, D. A., Ben-Zeev, D., Tseng, V. W., Kane, J. M., Brian, R., Campbell, A. T., Hauser, M., Scherer, E. A., & Choudhury, T. (2020). Predicting early warning signs of psychotic relapse from passive sensing data: An approach using encoder-decoder neural networks. *JMIR mHealth and uHealth*, 8(8).

Allsopp, K., Read, J., Corcoran, R., & Kinderman, P. (2019). Heterogeneity in psychiatric diagnostic classification. *Psychiatry Research*, 279(April), 15–22.

Barabási, A.-L. (2012). The network takeover. *Nature Physics*, 8, 14–16.

Bathelt, J., Geurts, H. M., & Borsboom, D. (2022). More than the sum of its parts: Merging network psychometrics and network neuroscience with application in autism. *Network Neuroscience*, 6, 445–466.

Beltz, A. M., Wright, A. G., Sprague, B. N., & Molenaar, P. C. (2016). Bridging the nomothetic and idiographic approaches to the analysis of clinical data. *Assessment*, 23, 447–458.

Borsboom, D. & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, 9, 91–121.

Burger, J., Van Der Veen, D. C., Robinaugh, D. J., Quax, R., Riese, H., Schoevers, R. A., & Epskamp, S. (2020). Bridging the gap between complexity science and clinical practice by formalizing idiographic theories: A computational model of functional analysis. *BMC Medicine*, 18(1), 1–18.

Caspi, A., Houts, R. M., Ambler, A., Danese, A., Elliott, M. L., Hariri, A., Harrington, H. L., Hogan, S., Poulton, R., Ramrakha, S., Rasmussen, L. J., Reuben, A., Richmond-Rakerd, L., Sugden, K., Wertz, J., Williams, B. S., & Moffitt, T. E. (2020). Longitudinal Assessment of Mental Health Disorders and Comorbidities Across 4 Decades Among Participants in the Dunedin Birth Cohort Study. *JAMA network open*, 3(4), e203221.

Coco, M. I. & Dale, R. (2014). Cross-recurrence quantification analysis of categorical and continuous time series: an r package. *Frontiers in Psychology*, 5, 510.

Cramer, A. O., Waldorp, L. J., Van Der Maas, H. L., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, 33(2-3), 137–150.

Dalmeida, K. M. & Masala, G. L. (2021). HRV Features as Viable Physiological Markers for Stress Detection Using Wearable Devices. *Sensors*, 21.

David, S. J., Marshall, A. J., Evanovich, E. K., & Mumma, G. H. (2018). Intraindividual Dynamic Network Analysis – Implications for Clinical Assessment. *Journal of Psychopathology and Behavioral Assessment*, 40(2), 235–248.

Dimensions (2018). Digital science. Software. Available from https://app.dimensions.ai.

Epskamp, S., van Borkulo, C. D., van der Veen, D. C., Servaas, M. N., Isvoranu, A. M., Riese, H., & Cramer, A. O. J. (2018a). Personalized network modeling in psychopathology: The importance of contemporaneous and temporal connections. *Clinical Psychological Science*, 6, 416–427.

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018b). The Gaussian Graphical Model in Cross-Sectional and Time-Series Data. *Multivariate Behavioral Research*, 53(4), 453–480.

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, 126(8), 1044–1056.

Fried, E. I. (2022). Studying Mental Health Problems as Systems, Not Syndromes. *Current Directions in Psychological Science*, 31(6), 500–508.

Grünerbl, A., Muaremi, A., Osmani, V., Bahle, G., Öhler, S., Tröster, G., Mayora, O., Haring, C., & Lukowicz, P. (2015). Smartphone-based recognition of states and state changes in bipolar disorder patients. *IEEE Journal of Biomedical and Health Informatics*, 19(1), 140–148.

Hagan, L. D. & Guilmette, T. J. (2015). Dsm-5: Challenging diagnostic testimony. *International Journal of Law and Psychiatry*, 42-43, 128–134.

Hernando, D., Roca, S., Sancho, J., Alesanco, Á., & Bailón, R. (2018). Validation of the apple watch for heart rate variability measurements during relax and mental stress in healthy subjects. *Sensors (Switzerland)*, 18(8).

Jones, P. J., Heeren, A., & McNally, R. J. (2017). Commentary: A network theory of mental disorders.

Jones, P. J., Ma, R., & McNally, R. J. (2019). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research*, 56, 353–367.

Jones, P. J., Mair, P., & McNally, R. J. (2018). Visualizing psychological networks: A tutorial in r.

Kalin, N. H. (2020). The critical relationship between anxiety and depression. *The American Journal of Psychiatry*.

Knight, A. & Bidargaddi, N. (2018). Commonly available activity tracker apps and wearables as a mental health outcome indicator: A prospective observational cohort study among young adults with psychological distress. *Journal of Affective Disorders*, 236, 31–36.

Kusnanto, H., Agustian, D., & Hilmanto, D. (2018). Biopsychosocial model of illnesses in primary care: A hermeneutic literature review. *Journal of Family Medicine and Primary Care*, 7(3), 497–500.

Lee, B. & Kim, Y.-E. (2022). Validity of the depression, anxiety, and stress scale (dass-21) in a sample of korean university students. *Current Psychology*, 41, 3937–3946.

Lui, G. Y., Loughnane, D., Polley, C., Jayarathna, T., & Breen, P. P. (2022). The Apple Watch for Monitoring Mental Health–Related Physiological Symptoms: Literature Review. *JMIR Mental Health*, 9(9).

Makara-Studzińska, M., Tyburski, E., Załuski, M., Adamczyk, K., Mesterhazy, J., & Mesterhazy, A. (2022). Confirmatory Factor Analysis of Three Versions of the Depression Anxiety Stress Scale (DASS-42, DASS-21, and DASS-12) in Polish Adults. *Frontiers in Psychiatry*, 12(January), 1–9.

Marwan, N. & Kraemer, K. H. (2023). Trends in recurrence analysis of dynamical systems. *The European Physical Journal Special Topics*, 232, 5–27.

Meyer, T. (2021). Analyze apple health data with python. Retrieved October 2023 from https://www.reyemsaibot.com/2022/01/06/analyze-apple-health-data-with-python/.

Molenaar, P. C. M. (2004). A Manifesto on Psychology as Idiographic Science: Bringing the Person Back Into Scientific Psychology, This Time Forever. *Measurement: Interdisciplinary Research & Perspective*, 2(4), 201–218.

Molenaar, P. C. M. & Valsiner, J. (2018). How generalization works through the single case: A simple idiographic process analysis of an individual psychotherapy. *Yearbook of idiographic science*, 1, 23–38.

Moncrieff, J., Cooper, R. E., Stockmann, T., Amendola, S., Hengartner, M. P., & Horowitz, M. A. (2022). The serotonin theory of depression: a systematic umbrella review of the evidence. *Molecular Psychiatry*, (June), 1–14.

njr0, tdda, & DaShoe (2021). applehealthdata. GitHub. Retrieved October 2023 from https://github.com/tdda/applehealthdata.

Olthof, M., Hasselman, F., Oude Maatman, F., Bosman, A. M. T., & Lichtwarck-Aschoff, A. (2023). Complexity theory of psychopathology. *Journal of Psychopathology and Clinical Science*, 132(3), 314–323.

Osman, A., Wong, J., Bagge, C., Freedenthal, S., Gutierrez, P., & Lozano, G. (2012). The Depression Anxiety Stress Scales-21 (DASS-21): Further Examination of Dimensions, Scale Reliability, and Correlates. *Journal of Clinical Psychology*, 68(12), 1322–1338.

Pang, J., Tang, X., Li, H., Hu, Q., Cui, H., Zhang, L., Li, W., Zhu, Z., Wang, J., & Li, C. (2019). Altered interoceptive processing in generalized anxiety disorder—a heartbeat-evoked potential research. *Frontiers in Psychiatry*, 10, 451395.

Patel, D. & Saunders, D. (2018). Apps and wearables in the monitoring of mental health disorders. *British Journal of Hospital Medicine*, 79, 672–5.

Perini, G., Ramusino, M. C., Sinforiani, E., Bernini, S., Petrachi, R., & Costa, A. (2019). Cognitive impairment in depression: Recent advances and novel treatments. *Neuropsychiatric Disease and Treatment*, 15, 1249–1258.

Qualtrics Development Company (2005). Qualtrics.

Radicchi, F., Castellano, C., Cecconi, F., & Parisi, D. (2004). Defining and identifying communities in networks. *Proceedings of the National Academy of Sciences*, 101(9), 2658–2663.

Shaffer, F. & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms.

Turner, J. R. & Baker, R. M. (2019). Review complexity theory: An overview with potential applications for the social sciences. *Systems*, 7(1).

Van den Bergh, N., Marchetti, I., & Koster, E. H. (2021). Bridges over Troubled Waters: Mapping the Interplay Between Anxiety, Depression and Stress Through Network Analysis of the DASS-21. *Cognitive Therapy and Research*, 45(1), 46–60.

Wainberg, M. L., Scorza, P., Shultz, J. M., Helpman, L., Mootz, J. J., Johnson, K. A., Neria, Y., Bradford, J. M. E., Oquendo, M. A., & Arbuckle, M. R. (2017). Challenges and opportunities in global mental health: a research-to-practice perspective.

Wallot, S. & Leonardi, G. (2018). Analyzing multivariate dynamics using cross-recurrence quantification analysis (crqa), diagonal-cross-recurrence profiles (dcrp), and multidimensional recurrence quantification analysis (mdrqa) - a tutorial in r. *Frontiers in Psychology*, 9.

Whooley, O. (2014). Nosological reflections: The failure of dsm-5, the emergence of rdoc, and the decontextualization of mental distress. *Soc Ment Health*, 4.

Wichers, M. & Groot, P. C. (2016). Critical Slowing Down as a Personalized Early Warning Signal for Depression. *Psychotherapy and Psychosomatics*, 85(2), 114–116.

A Appendix

DASS21

Name: Date:

Please read each statement and circle a number 0, 1, 2 or 3 which indicates how much the statement applied to you **over the past week**. There are no right or wrong answers. Do not spend too much time on any statement.

The rating scale is as follows:

0 Did not apply to me at all
1 Applied to me to some degree, or some of the time
2 Applied to me to a considerable degree or a good part of time
3 Applied to me very much or most of the time

1 (s)	I found it hard to wind down	0	1	2	3
2 (a)	I was aware of dryness of my mouth	0	1	2	3
3 (d)	I couldn't seem to experience any positive feeling at all	0	1	2	3
4 (a)	I experienced breathing difficulty (e.g. excessively rapid breathing, breathlessness in the absence of physical exertion)	0	1	2	3
5 (d)	I found it difficult to work up the initiative to do things	0	1	2	3
6 (s)	I tended to over-react to situations	0	1	2	3
7 (a)	I experienced trembling (e.g. in the hands)	0	1	2	3
8 (s)	I felt that I was using a lot of nervous energy	0	1	2	3
9 (a)	I was worried about situations in which I might panic and make a fool of myself	0	1	2	3
10 (d)	I felt that I had nothing to look forward to	0	1	2	3
11 (s)	I found myself getting agitated	0	1	2	3
12 (s)	I found it difficult to relax	0	1	2	3
13 (d)	I felt down-hearted and blue	0	1	2	3
14 (s)	I was intolerant of anything that kept me from getting on with what I was doing	0	1	2	3
15 (a)	I felt I was close to panic	0	1	2	3
16 (d)	I was unable to become enthusiastic about anything	0	1	2	3
17 (d)	I felt I wasn't worth much as a person	0	1	2	3
18 (s)	I felt that I was rather touchy	0	1	2	3
19 (a)	I was aware of the action of my heart in the absence of physical exertion (e.g. sense of heart rate increase, heart missing a beat)	0	1	2	3
20 (a)	I felt scared without any good reason	0	1	2	3
21 (d)	I felt that life was meaningless	0	1	2	3

DASS-21 Scoring Instructions

The DASS-21 should not be used to replace a face to face clinical interview. If you are experiencing significant emotional difficulties you should contact your GP for a referral to a qualified professional.

Depression, Anxiety and Stress Scale - 21 Items (DASS-21)

The Depression, Anxiety and Stress Scale - 21 Items (DASS-21) is a set of three self-report scales designed to measure the emotional states of depression, anxiety and stress.

Each of the three DASS-21 scales contains 7 items, divided into subscales with similar content. The depression scale assesses dysphoria, hopelessness, devaluation of life, self-deprecation, lack of interest / involvement, anhedonia and inertia. The anxiety scale assesses autonomic arousal, skeletal muscle effects, situational anxiety, and subjective experience of anxious affect. The stress scale is sensitive to levels of chronic non-specific arousal. It assesses difficulty relaxing, nervous arousal, and being easily upset / agitated, irritable / over-reactive and impatient. Scores for depression, anxiety and stress are calculated by summing the scores for the relevant items.

The DASS-21 is based on a dimensional rather than a categorical conception of psychological disorder. The assumption on which the DASS-21 development was based (and which was confirmed by the research data) is that the differences between the depression, anxiety and the stress experienced by normal subjects and clinical populations are essentially differences of degree. The DASS-21 therefore has no direct implications for the allocation of patients to discrete diagnostic categories postulated in classificatory systems such as the DSM and ICD.

Recommended cut-off scores for conventional severity labels (normal, moderate, severe) are as follows:

NB Scores on the DASS-21 will need to be multiplied by 2 to calculate the final score.

	Depression	**Anxiety**	**Stress**
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

Lovibond, S.H. & Lovibond, P.F. (1995). Manual for the Depression Anxiety & Stress Scales. (2nd Ed.)Sydney: Psychology Foundation.

Participant Information Sheet

Introduction

You are invited to participate in a research study into physiological and affective aspects of mood. Before you decide whether or not to participate, it is important that you understand the purpose of the study, what your participation will entail, and your rights as a participant.

Purpose of the Study

The research aims to assess physiological and affective states using wearable technologies and questionnaires to gain a better understanding of mental health (care).

Study Procedures

- If you choose to participate, you will be asked to fill in a questionnaire about your mood and stress level twice a day, lasting approximately 5 minutes, over a period of 15 days
- You will also be asked to wear an Apple watch that keeps track of your heart rate during the day

Risks and Benefits

There are no known risks associated with participating in this study. The potential benefits include getting a personal insight in your mood state.

Confidentiality

All data collected during this study will be kept strictly confidential. Your responses will be anonymous, and your personal information will not be disclosed to anyone outside the research team. In the event of a medically relevant finding in your physiological data, we will inform you so medical advice can be won from a medical doctor.

Voluntary Participation

Participation in this study is entirely voluntary. You may choose to withdraw from the study at any time without any penalty and you do not have to provide the researchers with a reason. Your decision to participate or withdraw will not affect your relationship with the researchers or the University of Leiden.