The Psychometric Network Structure of Mental Health in the General Population

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Abstract

Mental health is not only defined by the absence of psychological distress, but also by the presence of well-being. The two continua model supports this view. Psychometric network analysis allows identifying the most central domains of mental health and the most central underlying symptoms that make up these domains, which are assumed to have the strongest influence on the entire network. Previous studies mainly investigated clinical samples or aspects of overall mental health, while the current study aims to research the network structure of overall mental health in the general population.

Psychometric networks were estimated (N = 1663) on the domain level, and on a domain/symptom level. Centrality, bridge centrality, and the general structure of the network were investigated, and differences between genders and marital status were explored.

In both the networks (domain level, and domain/symptom level), depression was the most central domain. In the network on the domain level, that was followed by anxiety, and in the network that combines the domain and symptom level, mastery and personal growth also had high centralities. Bridge nodes were depression and emotional well-being (domain level), and depression and paranoid ideation (symptom level). No differences were found between the network structure of men and women. Between married and not married participants, differences in global strength were identified, with higher strength centralities for social well-being and psychoticism in the network of not married participants.

The findings confirm the two continua model, as it became apparent that psychological distress and well-being are two separate constructs, which are nevertheless correlated and influence each other. Further, the study broadens the understanding of overall mental health in the general population. Results can be used to develop effective and efficient interventions to improve mental health in the general population.

Keywords: psychometric network structure, mental health, psychological distress, well-being

Mental Illness and Mental Well-being

Mental health is a complex construct with many different facets. The two continua model of mental health offers a perspective that includes both, well-being and psychological distress, which are separate but related entities (Keyes, 2002, 2005). This study aims to further increase understanding of mental health in the general population, by investigating its network structure. For this, psychometric network analysis is used to analyse how different domains and symptoms of mental health are correlated, and which are the most important to the entire network. Further, it will be investigated whether differences in network structure can be detected for different genders and differing marital statuses.

Mental health disorders are very common in the general population. The 12-month prevalence of mental disorders in the adult EU population is estimated to be 27% (Wittchen & Jacobi, 2005). In the diagnostic and statistical manual of mental disorders (American Psychiatric Association, 2013), more than 150 mental disorders are categorised. Out of these, anxiety and mood disorders are most common, with a lifetime prevalence of around 12.9% (anxiety disorders) and 9.6% (mood disorders) (Steel et al., 2014). When people are diagnosed with a mental disorder, they are more likely to suffer from another mental disorder as well (Andrews et al., 2002; Plana-Ripoll et al., 2019). An important consequence of mental illness is the stigma that affected people experience. People who suffer from mental illness get stigmatized by others, but also stigmatize themselves. Stereotypes, prejudices, and discrimination negatively affect various life domains, for example, work, social life, and health care (Rüsch et al., 2005).

However, also people who are not diagnosed with a mental health disorder suffer from psychological pathological symptoms. This means people experience psychological distress in different pathological domains, and the level of their psychological distress can vary even within a healthy population. This kind of psychological distress will be the focus of this study.

Mental health is often explained in terms of an absence of psychological distress, but this perspective is not exhaustive, as the presence of well-being is another critical component of mental health. The World Health Organisation defines a mentally healthy person as someone who is able to "realize his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community" (WHO, 2018). As it gets clear in this definition, complete mental health entails not only low levels of psychological distress but also positive resources, specifically well-being.

Well-being consists of three domains, namely emotional, social, and psychological (Keyes, 2002). Emotional well-being is a combination of positive affect, avowed happiness and avowed life satisfaction (Keyes, 2005, 2007). Keyes (1998) describes social coherence, social acceptance, social actualisation, social contribution, and social integration as the five aspects of social well-being. Psychological well-being encompasses autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, and self-acceptance (Ryff & Keyes, 1995). High scores on these well-being domains are positively related to flexible and creative thinking, pro-social behaviour, and good physical health (Huppert, 2009).

As it gets clear, when investigating mental health, both psychological distress and well-being need to be considered, as well as their connection to each other. Only this broader focus reflects a holistic perspective of mental health.

The Two Continua Model of Mental Health

A model based on the WHO definition and this more complete perspective is the two continua model. It proposes that the two dimensions of mental illness and well-being are separate but related (Keyes, 2002, 2005). In other words, these two entities are distinct from each other, meaning that a person can score high on psychological distress, but also high on well-being (or vice versa) (Keyes, 2002, 2005). High functioning on well-being does not necessarily mean low functioning on psychological distress. Yet, psychological distress and well-being are correlated (Keyes, 2002, 2005). In the general population, these two dimensions are moderately correlated (Lamers et al., 2011). In practice, this means that people with an absence of mental health are categorised as languishing, whereas people who score high in psychological, social, and mental well-being are categorised as flourishing (Keyes, 2002, 2005).

The validity of the two continua model, as described above, has been tested in many studies. For instance, Gilmour (2014) found only moderate correlations between common mental disorders and overall mental health, which supports that the absence of mental disorders does not sufficiently account for complete mental health. The same study also shows that more people who are languishing than people who are flourishing suffer from mental illnesses, which highlights that well-being and psychological distress are related (Gilmour, 2014). Keyes (2005) performed a confirmatory factor analysis, which revealed that the two-factor oblique model (which describes mental health and mental illness as two distinct, but correlated factors), fits their data of the general population best. Lamers et al. (2011) also studied the general population and performed a confirmatory factor analysis. Their results are in line with Keyes (2005), as they found the same model to fit their data best (Lamers et al., 2011). That well-being and psychological distress are distinct, yet related, was also found for patients suffering from mood disorders, anxiety disorders, personality disorders, and developmental disorders (Franken et al., 2018). Interestingly, correlations between well-being and psychological distress were highest in mood disorders, followed by anxiety disorders (Franken et al., 2018).

Goodman et al. (2018) relate different domains of well-being (i.e. positive emotions, meaning and purpose in life, social relationships) to different domains of psychological distress such as depression, bipolar disorder, and social anxiety disorder. By doing this, they highlight that people with psychological disorders can also have high levels of well-being, and some domains of well-being can be even higher in people with certain psychological disorders, than in healthy people. For example, people diagnosed with bipolar disorder typically experience greater positive emotions than healthy persons when they are in a hypomanic or manic state (Goodman et al., 2018). This highlights the importance of taking both, well-being and psychological distress into account during treatment. However, Goodman et al. (2018) relate different psychological disorders to different well-being domains but do not investigate relationships between the disorders, or between different well-being domains.

Currently, validation of the two-continua model is mostly based on factor analyses (Keyes, 2005; Lamers et al., 2011), which is rooted in the assumption that a factor causes the symptoms of a disorder. However, this does not reflect reality, as multiple factors can influence how symptoms develop, and these factors also influence each other (e.g. Beard et al., 2016; Snippe et al., 2017). Further, each of the factors is a latent variable, which means that it is not certain whether they are causing the symptoms, or if they are a collection of symptoms that make up that factor (Borsboom et al., 2016). Investigating the two continua model from a network perspective (instead of traditional factor analyses) could therefore extend the current knowledge of mental health.

Although studies show that psychological distress and well-being are related, it is unclear how they are related on a domain and underlying symptoms level. More concretely, the relationships between different domains and their symptoms, both within and between the two clusters remain unknown. Further, it is not clear whether there are differences in the relevance of the domains and underlying symptoms for experiencing mental health. In other words, it is uncertain whether one domain (e.g. anxiety) has more influence than another (e.g. psychoticism) on the remaining domains in the network. It is also unclear whether psychological distress or well-being is more important for overall mental health. Lastly, it remains unknown whether certain symptoms (e.g. self-acceptance, personal growth, mastery) are more relevant than others within one domain (e.g. psychological well-being). In summary, our current understanding of mental health, and specifically how the domains and symptoms are related to each other, is not sufficient yet.

Psychometric Network Theory

Another way to think about psychological distress is to view it in terms of a network of symptoms which maintain each other. Certain symptoms can be present in different kinds of disorders, so the disorders can overlap in some cases and it might be more accurate to explain disorders in terms of their symptoms. To integrate this perspective, and expand our knowledge about mental health, psychometric network theory can be a helpful approach. This integrates the idea, that symptoms in a network that are close in the network structure, maintain each other. Consequently, clustered symptoms (i.e. belonging to the same disorder) in a network will sustain each other (Borsboom, 2017). Four principles support this idea. First, *complexity* means that the interactions between different components in a psychological distress network are crucial to describe mental diseases. Next, *symptom-component correspondence* highlights that the network is composed of symptoms, which are used in current diagnostic manuals. The third principle highlights that *direct causal connections* between symptoms make up the structure of the network. In other words, the structure depends on which nodes are correlated in what way with the others. The last principle is called *mental disorders follow network structure*, and describes that some symptoms have a stronger connection than others, which leads to clusters of symptoms which typically arise together (Borsboom, 2017). For example, symptoms that belong to the same disorder are more likely to occur together than symptoms of different disorders. This last principle cannot only be applied to psychological distress, but also to mental health.

This approach seems to reflect the reality of mental health more accurately than analyses based on factor analysis. Compared to factor analysis, network analysis adds complexity by taking into account the interplay between different symptoms and their correlations within the network, instead of assuming that individual factors cause a disease. Psychometric network analysis allows for a better insight into how the symptoms, both well-being and psychological distress are associated with each other, which leads to a more complete and precise understanding of mental health. This can be done by identifying symptoms and associations between them, which are then displayed in a network (Borsboom, 2017). Symptoms are shown as *nodes*, and the interactions between them are shown by connections (i.e. *edges*) between the nodes (Borsboom, 2017). When displayed as a graph, the network's nature can be visualized.

Furthermore, novel insights can be drawn from using network analysis. For example, it gives information about the symptom's centrality, which displays the importance of a symptom in the context of the entire network, for example by indicating how influential the symptom is (Opsahl et al., 2010). Network analysis also gives insight into which symptoms are clustered, meaning which symptoms are close to each other in the network and therefore are more likely to emerge together (Jones et al., 2019). Bridge centrality, meaning which symptoms are most important (have strong associations) between clusters, can give insights into how symptoms or clusters of symptoms (in this case, mental health domains) are related (Jones et al., 2019).

Psychometric Network Structures of Mental Health

Several studies examining the network structure of mental health or illness exist. However, they mostly focus on psychological distress. Therefore, studies were often conducted in a clinical sample with specific disorders or groups of disorders, for example, depression (Snippe et al., 2017) or eating disorders (de Vos et al., 2021). Many studies also researched the interaction between depression and anxiety (e.g. Beard et al., 2016; Bekhuis et al., 2016), with a focus primarily on a clinical population. Beard and colleagues (2016) found sad mood, low energy, anhedonia, and guilt/worthlessness to be central depression symptoms, while too much worry, unable to control worry, and unable to relax were most central in anxiety.

Besides studying networks of psychological distress, researchers also examined networks of well-being (Blasco-Belled & Alsinet, 2021; Zeng et al., 2019). Self-acceptance (Blasco-Belled & Alsinet, 2021), cheerfulness, engagement in current activity, and optimism (Zeng et al., 2019) were identified as the most central symptoms of well-being.

However, the number of studies that include both psychological distress and well-being in a mental health network is limited. One example is a study by Campbell and Osborn (2021), who researched psychological distress and psychological well-being in Kenyan adolescents. The main findings confirm that psychological distress and well-being are related but distinct, and identify ‘family provides emotional help and support’ and ‘self-blame’ as the most central nodes in the network. The most important bridge nodes were ‘family helps me’ and ‘I can talk to family about problems’ (Campbell & Osborn, 2021). In another study, Zeiler et al. (2021) performed a network analysis for psychopathological symptoms and well-being in overweight and underweight adolescents. They found anxious/depressed mood and attention problems as most central in the network. De Vos et al. (2021) studied mental health networks for eating disorder patients and found that mental well-being and psychological distress are related, but change in one of these domains does not determine change in the other. Further, they found psychological well-being to be the most central domain in the mental health network, followed by emotional well-being and general psychopathology.

These few studies relate psychological distress and well-being in network analyses. However, the samples are relatively narrow, as they either only include adolescents (Campbell & Osborn, 2021; Zeiler et al., 2021) and/or study a specific clinical population (de Vos et al., 2021; Zeiler et al., 2021). Further, Campbell and Osborn (2021) only measured psychological well-being, and not emotional or social well-being. Because of these factors, one cannot draw conclusions about the general population, and a mental health network analysis for this group is needed. This could help to identify how to improve mental health for a large target group by highlighting potential domains and symptoms to target in interventions in the general population.

A study about mental health networks in the general population, which includes both psychological distress and well-being could further validate the two continua model and provides more information about the network structure and centrality of the domains. Previous studies found certain central symptoms for specific disorders (e.g. depression, anxiety) in a clinical population, and some central symptoms for (psychological) well-being in a sample of the general population were identified. However, these findings are specific to certain disorders, certain kinds of well-being, or certain populations. Therefore, it remains unclear which domains are most influential in an overall mental health network of the general population. By extending mental health network studies to the general population, results could be used to improve overall mental health for example by prevention interventions for mental illness, or by actively reinforcing central domains of mental well-being. Further, mental health programs could combine psychological distress and well-being treatments, to increase their effectiveness.

The Present Research

The aim of this research is to increase understanding of the mental health of the general population from a network perspective, as well as to expand the knowledge of the relationships between psychological distress and well-being. To gain a better understanding of mental health, a psychometric network analysis of mental health will be performed, by including well-being and psychological distress domains in a network. Additionally, a network that includes psychological distress domains, and well-being symptoms will be estimated. The overall network structure, as well as centrality and bridge centrality between well-being and psychological distress, will be estimated.

As gender and marital status have shown to be important determinants of mental health, these categories will be of special interest and networks for subcategories of these will be compared. Previous studies showed that women are more often affected by mental disorders than men (Steel et al., 2014) and that people who are married suffer less from psychological disorders and are happier than people who are not married (Wilson & Oswald, 2005). Psychometric networks do not show whether one group is more affected by certain symptoms or domains but show the structure of the symptoms. In other words, comparing the networks of different groups can give insight into whether there are differences in how the domains and symptoms relate to each other. This knowledge can be used to target interventions or prevention programs more specifically.

This results in the following research questions:

RQ1: What are the most central domains and symptoms within a mental health network in the general population?

RQ2: Which nodes have the highest bridge centrality between psychopathological and well-being domains?

RQ3: Are there differences in network structure and node strength centrality between females and males?

RQ4: Are there differences in network structure and node strength centrality between people who are married, and people who are not married?

Methods

Participants

For this study, data from the LISS panel of CentERdata was used. This internet panel for longitudinal internet studies in the social sciences is managed by CentERdata in Tilburg (NL). The LISS panel is representative of 5000 Dutch households, which are randomly selected. Participants are provided with internet access and a computer if necessary, to fill out monthly online questionnaires. Compared to national statistics, the elderly, single, never married persons, widowers and immigrants are underrepresented in the LISS panel. The dataset used in this study was collected in December 2007 and consists of 1663 participants, with the age from 18 to 108 years (M_{age} = 47.65, *SD* = 17.8). The participant's gender was evenly distributed, with 49.8 % (*N* = 828) male, and 50.2 % (*N* = 835) female participants. 31.6% (*N* = 526) of the sample were not married, and 68.4% (*N* = 1137) were married.

Measures

Well-being and psychological distress were measured with two different questionnaires. For well-being, the Mental Health Continuum – Short Form was used, which consists of 14 items. These items can be understood as underlying symptoms of three well-being domains (emotional, social, psychological). The emotional well-being domain consists of the symptoms happiness, interested in life, and life satisfaction. Social well-being contains the underlying symptoms social contribution, social integration, social actualization, social acceptation, and social coherence. Lastly, the domain psychological well-being is made up of the symptoms self-acceptance, mastery, positive relations, personal growth, autonomy, and purpose in life. The questions were answered on a 6-Point Likert Scale, ranging from 0 (*never*) to 5 (*every day*). Example items were "*During the past month, how often did you feel interested in life*" or "*During the past month, how often did you feel that you liked most parts of your personality*". The internal consistency in this sample was high with α = .89 (emotional well-being: α = .82; social well-being: α = .74; psychological well-being: α = .83).

Psychological distress was measured with the Brief Symptom Inventory (Derogatis, 2001), which consists of 53 items, which can be grouped into 9 domains (aspects of psychological distress). These domains are the following: Somatization, Obsession-Compulsion, Interpersonal Sensitivity, Depression, Anxiety, Hostility, Phobic Anxiety, Paranoid Ideation and Psychoticism. All items were answered on a 5-Point Likert Scale ranging from 0 (*not at all*) to 4 (*extremely*). Example items were "*how much were you distracted by feeling weak in parts of your body during the past week?*" and "*how much were you distracted by feeling lonely during the past week?*" Internal consistency of the questionnaire is high, with Cronbach's alphas of the subscales ranging between .73 and .81, with the exception of .59 (Psychoticism) and .67 (Phobic Anxiety) (Lamers et al., 2011).

Data Analysis

All analyses were conducted in R (Appendix B). Analyses were conducted first on a domain level, because the dataset does not entail data on the symptom (i.e. items) level for psychological distress (only for well-being), and including every item separately would lead to a too complex network. However, one network with the domains of psychological distress, and the symptoms of well-being was calculated, to get more detailed information on the overall network. It is important to note here, that the underlying symptoms of well-being that are included in this network might have further underlying aspects that make up these symptoms. For instance, the well-being symptom personal growth could be measured with multiple items and would have further subcategories.

Before the main analysis, it was tested whether the domains of the questionnaires actually measure different domains, or if their correlations to other domains overlap too much. For this, the goldbricker function was used, which is part of the R *networktools* package (Jones, 2020). With this function, correlations of one node (e.g. depression) to all the other nodes, get compared to the correlations of another node (e.g. anxiety) to all the other nodes. This leads to a proportion of correlations, and if it is significantly different to the others, it can be assumed that the two nodes measure different domains (or symptoms), as their correlations to the other domains are unique. If the proportion of correlations is not significantly different, including both nodes in the analysis would not add valuable information (Levinson et al., 2018). Based on previous literature, a cut-off point of .25 for this significant proportion was chosen with a p-value of .01 (Levinson et al., 2018). This means it was computed for which node pairs less than 25% of the correlations were significantly different. For the networks on domain level, all node pairs were significantly different and no node had to be excluded. However, for the network on a domain and symptom level, two pairs of symptoms were identified that do not have significantly different proportions of correlations. These were anxiety and obsession-compulsion with a proportion of correlations of .143, and interpersonal sensitivity and obsession-compulsion with a proportion of correlations of .238. Both values are below the cut-off point of .25. Because of this, obsession-compulsion was excluded from the further analysis for the network on domain and symptom level.

Before proceeding with the analysis, five groups were created (*everyone, female, male, married, not married*), so that potential differences between gender and marital status can be detected later in the analysis. Then, networks for each group were estimated by using the package *qgraph* (Epskamp et al., 2012). For this analysis, graphical least absolute shrinkage and selection operator (glasso) was used, which is an algorithm for estimation of a sparse inverse covariance matrix (Friedman et al., 2008). This was combined with the Extended Bayesian Information Criterion (EBIC), which is a criterion for model selection that takes into account both the number of unknown parameters and the complexity of the model space (Chen & Chen, 2008). These are used to estimate a regularized Gaussian graphical model (GGM) (Epskamp et al., 2018). In this approach, low correlations and non-significant edges are reduced to zero, so false positive errors will be avoided and networks are easier to interpret (Epskamp et al., 2018). Consequently, only significant edges/correlations will be displayed in the results, and no p-value is reported for this. Within each network, it was differentiated between well-being and psychological distress.

Another network for the entire sample was calculated. For this, the same psychological distress domains were used, but to create a network structure with a more balanced number of nodes in each community, well-being symptoms instead of domains were used. This poses a challenge, as the nature of the variables in the network changes: the variables of the well-being cluster become ordinal variables (as they are measured as single items with Likert scales), and the ones of the psychological distress cluster are continuous (as they represent the scale score of a number of items). Because of this, the R package *MGM* is used for this network. This has the advantage, that a graphical model with mixed variables can be computed, without losing any information by transforming variables into another variable type (Haslbeck & Waldorp, 2015).

Next, centrality was estimated. Centrality is based on a combination of the strength (also called degree), closeness, and betweenness of the nodes (Freeman, 1978; Opsahl et al., 2010). However, previous studies recommend only the use of strength centrality in psychometric networks (Bringmann et al., 2019; Forbes et al., 2017, Isvoranu & Epskamp, 2021), which is why this is the only centrality measure used in this study. *Strength* refers to the sum of the edge-weights of the node, with another node (Freeman, 1978). Centrality values get standardized, and values higher than 1 standard deviation above the mean are considered high in the context of this study. The R package *qgraph* was used to measure centrality for each network and to plot the according graphs. To test how well-being and psychological distress are connected, bridge domains between these two groups were identified. Bridge domains are the nodes of one cluster (e.g. psychological distress) with the strongest connection to the nodes in the other cluster (e.g. well-being). For this, bridge (strength) centrality was estimated (Jones et al., 2019), by using the R package *networktools* (Jones, 2020).

To check whether the networks are stable and show accurate results, a stability analysis was conducted (Epskamp et al., 2018). This was done by using the R package *bootnet* (Epskamp et al., 2018). To calculate centrality stability, the network is estimated 1000 times, each time with only 75% of the original dataset. Then, it is checked how consistent these networks are. If the different networks have little variation, they are considered accurate, and if their interpretation remains similar with fewer observations, the original network is considered stable (Epskamp et al., 2018). To estimate edge weights accuracy, a 95% confidence interval with 1000 bootstraps was used. Then, stability of strength centrality was estimated with the correlation-stability coefficient (*CS*) with 1000 bootstraps. The correlation-stability coefficient is an indicator of the maximum proportion of cases that can be dropped, such that with a 95 % probability the correlation (*cor*) between original centrality indices and centrality of networks based on subsets is 0.7 or higher (Epskamp et al., 2018). In other words, it indicates how much of the original sample could be excluded, while still ensuring high correlations between the original sample and the subsets.

To be considered stable, correlation-stability coefficients should preferably be above 0.5, but not below 0.25 (Epskamp et al., 2018).

Lastly, the R package *NetworkComparionTest* (Van Borkulo et al., 2016) was used to compare networks of different groups of demographics, namely gender and marital status. Differences between these groups were identified with a network invariance test, as well as a global strength invariance test. If significant differences were found, differences between individual edge weights and strength centralities were explored. However, if no difference was found in the overall network structure or global strength, these individual differences were not further investigated to avoid misleading conclusions. For all analyses, a p-value of < .05 indicates a significant difference.

Results

Overview of the data

Table 1 shows the means and standard deviations of the entire sample and the scores divided by gender and marital status, including p-values. Overall, the scores are similar for most domains, but significant differences could be found between genders for the domains *somatization*, *interpersonal sensitivity, anxiety,* and *phobic anxiety*. Between married and not married participants, significant differences were found for the domains *emotional well-being*, *obsession-compulsion*, *depression, anxiety*, *phobic anxiety*, *paranoid ideation,* and *psychoticism*. Generally, scores for *paranoid ideation* and *obsession-compulsion* are the highest within the psychological distress cluster, and *emotional well-being* has the highest scores within the well-being cluster. A comparison between these two clusters is not possible, due to the different scales that were used in the measurement.

Table 1

Means (M) and Standard Deviations (SD) of the Mental Health Domains

Domain	M (*SD*)			P^{fm}	M (*SD*)		P^{nm}
	Everyone	Male	Female		Not married	Married	
Emotional Well-being	4.67 (*.94*)	4.64 (.96)	4.70 (*.92*)	.179	4.52 (*1.01*)	4.74 (*.90*)	<.001*
Social Well-being	3.33 (*1.01*)	3.33 (.99)	3.32 (*1.03*)	.806	3.39 (*1.02*)	3.29 (*.99*)	.064
Psychological Well-being	4.18 (*.99*)	4.15 (*.01*)	4.22 (*.98*)	.119	4.21 (*.97*)	4.17 (*1.00*)	.423
Somatization	.33 (*.42*)	.29 (*.39*)	.37 (*.44*)	<.001*	.34 (*.41*)	.32 (*.43*)	.281
Obsession-Compulsion	.52 (*.50*)	.51 (*.52*)	.53 (*.49*)	.506	.59 (*.54*)	.49 (*.49*)	<.001*
Interpersonal Sensitivity	.41 (*.51*)	.36 (*.47*)	.47 (*.54*)	<.001*	.44 (*.53*)	.40 (*.51*)	.215
Depression	.39 (*.48*)	.37 (*.46*)	.40 (*.49*)	.138	.49 (*.56*)	.34 (*.44*)	<.001*
Anxiety	.34 (*.43*)	.30 (*.40*)	.38 (*.46*)	<.001*	.39 (*.47*)	.32 (*.41*)	.002*
Hostility	.38 (*.41*)	.38 (*.43*)	.38 (*.39*)	.932	.36 (*.41*)	.38 (*.41*)	.316
Phobic Anxiety	.17 (*.33*)	.15 (*.29*)	.20 (*.36*)	.005*	.23 (*.37*)	.15 (*.30*)	<.001*
Paranoid Ideation	.50 (*.56*)	.52 (*.56*)	.49 (*.55*)	.205	.57 (*.59*)	.48 (*.54*)	.003*
Psychoticism	.31 (*.40*)	.30 (*.39*)	.31 (*.41*)	.794	.39 (*.45*)	.27 (*.37*)	<.001*

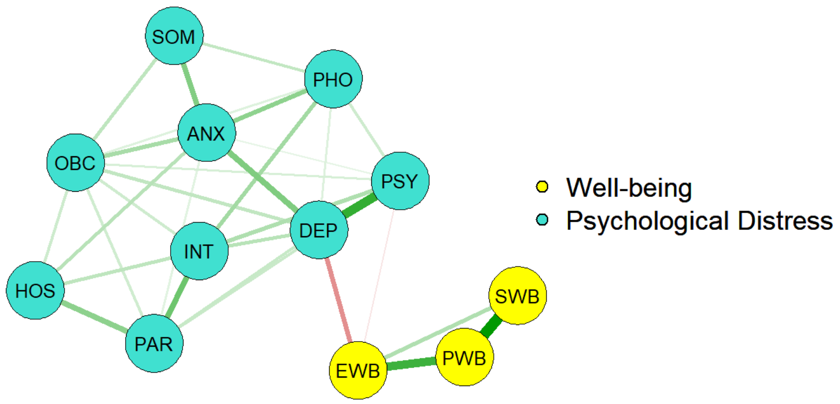
Note. * significant difference between mean values. p^{fm} = p-value for the difference between male and female participants. p^{nm} = p-value for the difference between not married and married participants

Mental Health Network (Domain Level)

The psychometric network of mental health of the entire sample is displayed in Figure 1. The network consists of 12 nodes and 31 edges. Two of the edges represent negative correlations, the other 29 edges positive ones. The strongest edges (*r* = correlations) were found between *psychological well-being* and *social well-being* (*r* = .49), *depression* and *psychoticism* (*r* = .40), and *psychological well-being* and *emotional well-being* (*r* = .38). The individual edge weights can be found in Table A1 (see Appendix A). A clear distinction between the two clusters (well-being and psychological distress) can be seen, as positive edges connect the nodes within these clusters, and the only two edges that connect the two clusters are the negative ones. The node strength centralities (*S*) are displayed in Table A2 in the Appendix. They are standardized z-scores, and every score that is larger than 1 (meaning it is more than 1 standard deviation above the nodes' mean centrality), is considered high. High strength centralities were found for *depression* (*S* = 1.99) and *anxiety* (*S* = 1.22). *Somatization* is the least central node in the network (*S* = -1.62) and therefore seems to be the least important domain in the network (see Figure 2). *Emotional well-being* and *depression* were found to be the domains with the highest bridge centrality (Figure A1 in Appendix). Accordingly, these domains most strongly connect the psychological distress cluster with the well-being cluster. They are negatively correlated (r = .-22).

Figure 1

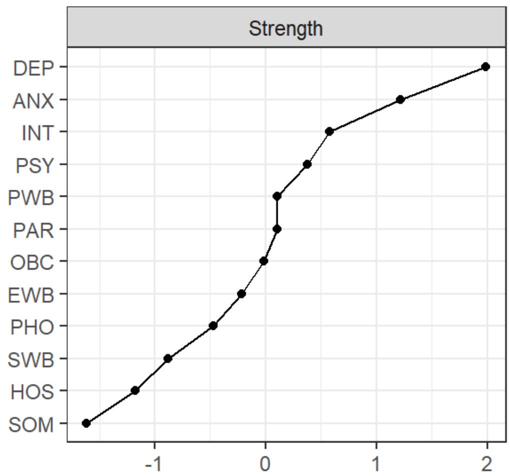
Psychometric Network of Mental Health for the Entire Sample (Domain Level)



Note. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = Emotional Well-being, PWB = Psychological Well-being, SWB = Social Well-being

Figure 2

Node Strength Centrality of the Network of the Entire Sample (Domain Level)



Note. Strength centrality reported in standardized scores on the x-axis. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = Emotional Well-being, PWB = Psychological Well-being, SWB = Social Well-being

Network Stability

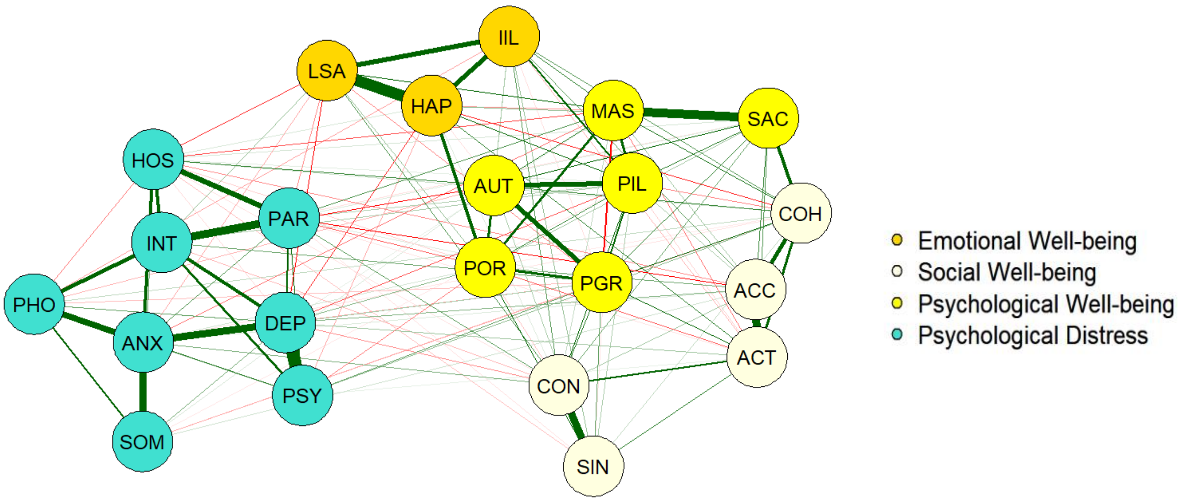
The edge-weight accuracy and centrality stability were estimated to check the stability of the network. For the network of the entire sample, the bootstrapped confidence intervals (CIs) of the edge-weights were considered stable, as they are relatively narrow, and edge-weight values of the sample largely overlap with the mean of the bootstrapped edge weights (see Figure A2). Strength centrality is also stable, with correlations between original centrality indices and centrality of the networks based on subsets of 0.7 or higher (*cor = 0.7*), as the correlation-stability coefficient indicates: CS(cor = 0.7) = .60 (Figure A3).

Mental Health Network (Domain and Symptom Level)

For the entire sample, a network was estimated which includes the domains of psychological distress, and the underlying symptoms of well-being. By choosing this approach, both clusters of the network will be more balanced in terms of the number of nodes. The network consists of 22 nodes and 78 edges. The well-being cluster consists of 14 nodes and the psychological distress cluster of 8 nodes. The strongest edges were found between *depression* and *psychoticism* (r = .42), *happiness* and *life satisfaction* (r = .39), and *mastery* and *self-acceptance* (r = .30). The individual edge weights are displayed in Table A3 (see Appendix A). For this network, the distinction between the two clusters is less clear than for the previous network. Although the strongest positive edges are within each cluster, negative edges are only weak and not only between the two clusters but also within. Weak positive edges also connect both clusters. Interestingly, a similar trend is observable for the well-being domains. Well-being symptoms generally have stronger nodes within one domain, yet no clear distinction between the domains can be identified. The node strength centralities (S) are displayed in Table A4 in the Appendix. The highest node centralities (larger than 1 standard deviation above the mean) were found for *depression* (*S* = 1.86), *mastery* (*S* = 1.59) and *personal growth* (*S* = 1.09). These nodes can therefore be considered the most important within the network, with the highest sums of the edge-weights with other nodes. The least central node was *somatization* (*S* = -2.47) and can be considered the least relevant within the network (see Figure 4). The highest bridge centrality was found for the nodes *paranoid ideation* and *depression* (Figure A6 in the Appendix), which means they have the strongest associations between the clusters of psychological distress and well-being.

Figure 3

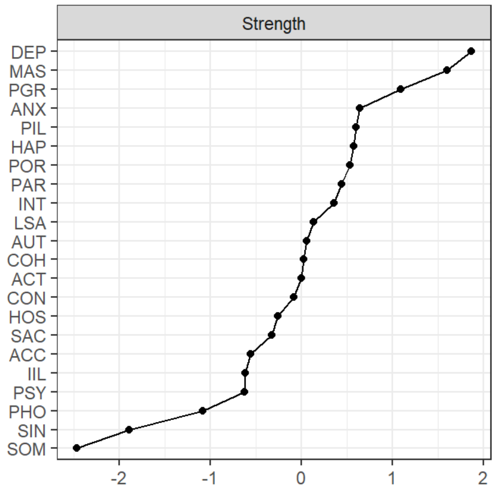
Psychometric Network of Mental Health for the Entire Sample (Domain and Symptom Level)



Note. HAP = Happiness, ILL = Interest in Life, LSA = Life Satisfaction, CON = Social Contribution, SIN = Social Integration, ACT = Social Actualization, ACC = Social Acceptation, COH = Social Coherence, SAC = Self-Acceptance, MAS = Mastery, POR = Positive Relations, PGR = Personal Growth, AUT = Autonomy, PIL = Purpose in Life, SOM = Somatization, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism

Figure 4

Node Strength Centrality of the Network of the Entire Sample (Domain and Symptom Level)



Note. Strength centrality reported in standardized scores on the x-axis. HAP = Happiness, ILL = Interest in Life, LSA = Life Satisfaction, CON = Social Contribution, SIN = Social Integration, ACT = Social Actualization, ACC = Social Acceptation, COH = Social Coherence, SAC = Self-Acceptance, MAS = Mastery, POR = Positive Relations, PGR = Personal Growth, AUT = Autonomy, PIL = Purpose in Life, SOM = Somatization, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism

Network Stability

The bootstrapped CIs of the edge-weights are stable, as they are relatively narrow and edge-weight values of the sample largely overlap with the mean of the bootstrapped edge weights (see Figure A4 in Appendix). Strength centrality is also stable, with correlations between original centrality indices and centrality of the networks based on subsets of 0.7 or higher (*cor = 0.7*), as the correlation-stability coefficient indicates: CS(cor = 0.7) = .58 (Figure A5 in Appendix).

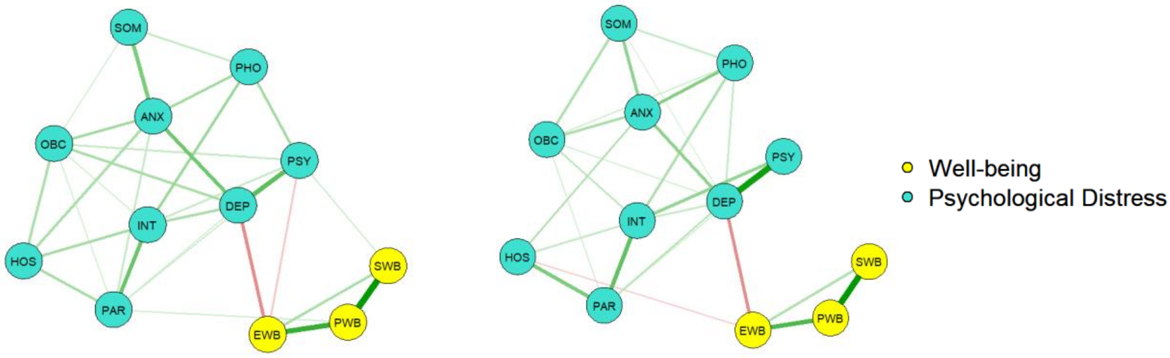
Mental Health Networks Divided by Gender

Next, to answer research question 3, two separate networks were calculated for the female, and the male participants (see Figure 5). The network of the female participants consists of 27 weighted edges and the network for male participants of 30 weighted edges.

The node strength centralities (*S*) are displayed in Table A5 in the Appendix. *Depression* is the most central node for males (*S* = 1.57), followed by *anxiety* (*S* = 1.26). For female participants, *depression* is the most central node as well (*S* = 2.51), followed by *interpersonal sensitivity* (*S* = .81) (Figure 6). These nodes can be therefore considered most important in the networks. In both networks, two of the edges are negative. In both cases, these negative edges connect well-being nodes and psychological distress nodes. In both networks, *emotional well-being* is negatively correlated with *depression*. In the network of the male participants, *emotional well-being* is also negatively correlated with *psychoticism*, whereas in the network of the female participants, there is a negative correlation between *emotional well-being* and *hostility*.

Figure 5

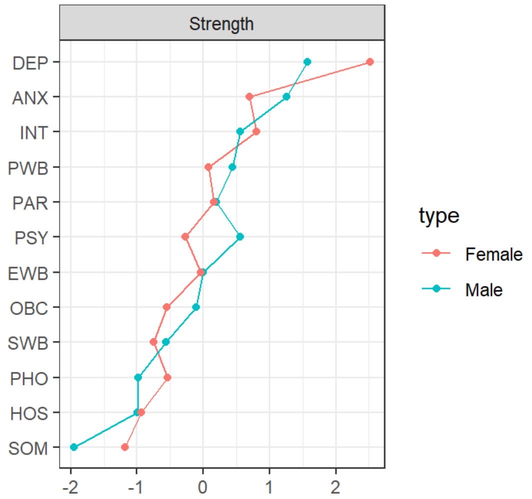
Psychometric Network of Mental Health for Male and Female Participants



Note. The network of male participants is shown at the left, and the network for female participants at the right. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = emotional well-being, PWB = psychological well-being, SWB = social well-being

Figure 6

Strength Centrality Plot of Network Structures, Divided by Gender



Note. Strength centrality reported in standardized scores on the x-axis. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = emotional well-being, PWB = psychological well-being, SWB = social well-being

Network Difference Test

Using the Network Comparison Test, the networks of male and female participants were compared. No significant mean differences (*Mdiff*) of the edge-weights between the networks could be found in the overall network structure (*Mdiff* = .18, *p* = .35). A significant difference in global network strength (*Sdiff*) could not be found either (*Sdiff* = .31, *p* = .30). Because no overall differences were found, specific differences between individual edges or centralities were not further investigated.

Network Stability

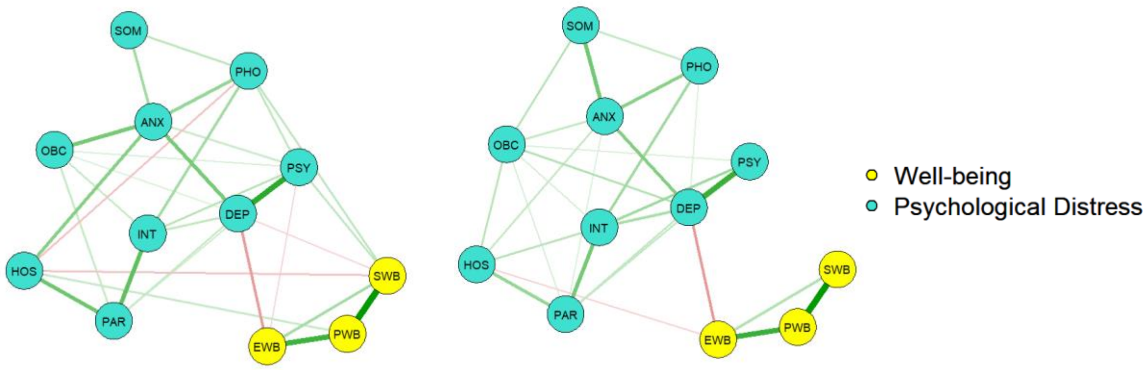
The bootstrapped CIs of the edge-weights are stable for both networks, as they are relatively narrow, and edge-weight values of the sample largely overlap with the mean of the bootstrapped edge weights in both cases (see Figure A7). Strength centrality is also stable, with correlations between original centrality indices and centrality of the networks based on subsets of 0.7 or higher (*cor = 0.7*), as the correlation-stability coefficient indicates for male participants (CS(cor = 0.7) = .56) and female participants (CS(cor = 0.7) = .60) (Figure A8 in Appendix).

Mental Health Networks Divided by Marital Status

Lastly, networks were calculated for participants who are not married, and for those who are married, to answer research question 4 (see Figure 7). The network of married participants consists of a total of 28 edges, with 2 negative ones. The network of not married participants consists of 31 edges, with 5 negative ones. The node strength centralities (*S*) are displayed in Table A6 in the Appendix. *Depression* is the most central node for married participants (*S* = 2.24), followed by *anxiety* (*S* = .98). For not married participants, *anxiety* (*S* = 1.23) and *depression* (*S* = 1.22) are the most central nodes as well (Figure 8). Accordingly, in both networks, depression and anxiety have the highest sums of the edge-weights with other nodes and can be considered most important for the entire network. Regarding strength centrality, the domains *anxiety*, *psychoticism*, and *social well-being* seem to be more important to the participants who are not married, than to the ones who are married.

Figure 7

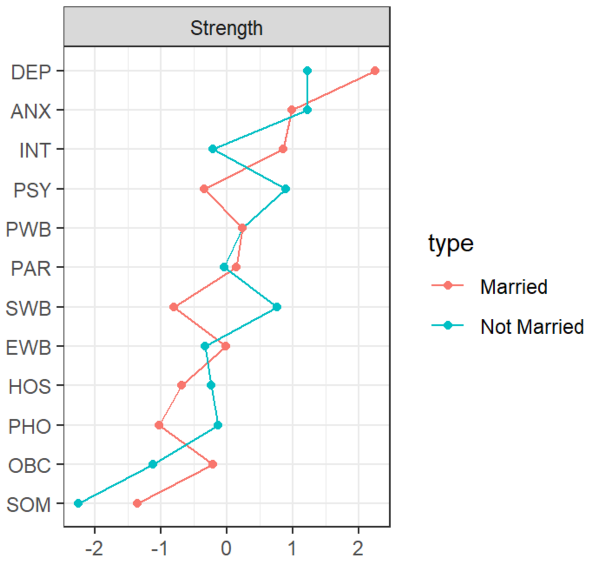
Psychometric Networks of Mental Health for Participants Divided by Marital Status



Note. The network of not married participants is shown at the left, and the network for married participants at the right. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = emotional well-being, PWB = psychological well-being, SWB = social well-being

Figure 8

Strength Centrality Plot of Network Structures, Divided by Marital Status



Note. Strength centrality reported in standardized scores on the x-axis. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = emotional well-being, PWB = psychological well-being, SWB = social well-being

Network Difference Test

Using the Network Comparison Test, the networks of married participants and participants who are not married were compared. No significant mean differences (*Mdiff*) of the edge-weights between the networks could be found in the overall network (*Mdiff* = .15, *p* = 1.0), so differences between individual edges were not further investigated. However, a significant difference in global network strength (*Sdiff*) was found between married and not married participants (*Sdiff* = .66, *p* < .05). Global strength for married participants was *S* = 4.91, and global strength centrality (*S*) for not married was *S* = 5.57. To be more specific, significant differences in strength centrality were found for social well-being (married: *S* = -.81; not married: *S* = .77, p < .01), and psychoticism (married: *S* = -.34; not married: *S* = .89, p < .01). This indicates that social well-being and psychoticism might be more important for the entire network for not married participants than for married participants. An overview of all node strength centralities can be found in Table A6 in the Appendix.

Network Stability

The bootstrapped CIs of the edge-weights are stable for both networks, as they are relatively narrow, and edge-weight values of the sample largely overlap with the mean of the bootstrapped edge weights in both cases (see Figure A9 in Appendix). Strength centrality is also stable, with correlations between original centrality indices and centrality of the networks based on subsets of 0.7 or higher (*cor = 0.7*), as the correlation-stability coefficient indicates for married participants (CS(cor = 0.7) = .60), and for participants who are not married (CS(cor = 0.7) = .46) (Figure A10 in Appendix). For not married participants this correlation-stability coefficient is below the desired cut-off point of .50, but still above .25. This means, it is less stable for not married participants than for the married participants, but still stable enough.

Discussion

The complex concept of mental health can be more easily understood in terms of the two continua model (Keyes, 2002). This model explains that well-being and psychological distress are related, yet distinct from each other. It is known that certain domains (of both well-being and psychological distress) can reinforce each other, but it is still unclear which domains play the most important role in the general population and how they are related. The present study is the first to examine this issue by investigating the structures of psychometric networks in the general population while including both well-being and psychological distress.

Psychometric Network Structure of Mental Health

Despite some differences, the overall networks are similar on a domain level, and on a domain/symptom level. Generally, in the present study, there are a lot of correlations between the domains (and items) in both networks, indicating that multiple factors are relevant for overall mental health. The network structure on the domain level supports the two continua model, by showing that the two clusters are distinct, yet related. This becomes clear because there are correlations between nodes of the two clusters, but they are negative. In the network on domain and symptom level, there are no strong negative correlations between the clusters. However, a distinction between them is still detectable, as the strong positive correlations are within the clusters, and not between them. Nevertheless, weaker correlations connect both clusters, which indicates that they are related to each other.

Further, the two continua model (Keyes, 2002) relates psychological distress and well-being, without indicating if one of them is more important than the other. Generally, the network structure of this sample on the domain level reveals that psychological distress may be more influential in mental health networks because domains of this cluster have higher strength centrality (i.e. are stronger connected to the other domains). However, it is important to keep in mind that in this network the number of psychological distress domains is three times higher than the number of well-being domains, which could have influenced this result as well. In contrast to that, in the network on the domain and symptom level, psychological distress and well-being are relatively balanced in terms of centrality, so no prominent differences can be seen in terms of which cluster contains more strongly connected domains/symptoms than the other. However, this result needs to be treated with caution, as well-being is measured with its symptoms, and psychological distress with its domains, which are each made up of a number of symptoms.

On both, domain and symptom/domain level, this study found depression to be most important in the network, and somatization to be least important. Overall, depression has the strongest connections to other domains in the network. On a domain level, anxiety was also found to have strong connections to the other domains. This is in line with Zeiler et al. (2021), who also found anxious/depressed mood to be most central in a network of psychological distress and well-being for overweight and underweight adolescents. Although this study includes the general population and not a clinical sample, its findings are in line with previous research. Especially depression has high comorbidity with other psychological distress symptoms in clinical samples (Rohde et al., 1991). From this, it can be assumed that similar processes happen within the overall population and that depressive symptoms affect (or are affected by) other domains as well.

Symptoms of depression like fatigue, negative thinking or loss of interest contribute to a downward spiral, which complicates recovery (Davey, 2014; Kennerly et al., 2016). Not being able to seek help, or engaging in everyday activities that would improve mental health, hinders a person with depressive symptoms to strive in several other life domains, which could be a reason why it is so important for the overall mental health network. Similar processes are relevant for anxiety. A person who suffers from anxiety will engage in “safety behaviours”, that prevent them from being exposed to situations that they are anxious about. However, avoiding these situations will hinder them from overcoming their anxiety (Kennerly et al., 2016). Similar to depressive symptoms, anxiety symptoms can lead to less engagement in everyday activities, as the affected person tends to avoid situations they become anxious in (Kennerly et al., 2016). Consequently, anxious symptoms can strongly influence several aspects of a person's life, and therefore many aspects within the mental health network.

However, other factors that are beyond the scope of this study could be the reason for this comorbidity as well. Examples of this are culture (Hwang et al., 2008) and biology (Renzi et al., 2018). Generally, psychometric network analysis can reveal which domains are strongly connected to other domains, but it is not possible to draw conclusions about the direction of the connection or influence. Therefore, it is not known whether for example, depression influences a lot of other domains, or if several domains in the network influence depression. In other words, the strong relationships between depression (and anxiety) and the rest of the network could be either the results of a large effect of depression (and anxiety) on the network, or it could be one of the reasons why the prevalence for depression (and anxiety) is so high, as it could be especially vulnerable to changes in the network.

Another reason for the strong relationships of depression and anxiety with other parts of the network could be the underlying symptoms of these domains. Unfortunately, the present study could not cover underlying symptoms of the psychological distress domains, but it is likely that symptoms of these domains overlap to a certain extent. For example, the domain anxiety probably has some similar underlying symptoms as the domain phobic anxiety, paranoid ideation, or obsession-compulsion, as they are all related to worrying and/or anxious feelings. Future research could further investigate this.

In the network on the domain and symptom level, mastery and personal growth were also high in centrality. Mastery is an important contributor to resilience (Montpetit & Tiberio, 2016). It includes taking care of daily tasks and is a form of control, which can make people less vulnerable to stress (Montpetit & Tiberio, 2016). De Vos et al. (2021) found environmental mastery, among others, to be an important bridge symptom between well-being and psychopathology in their symptom network for eating disorder patients. The sense of being able to change things, which is central to mastery, could give people the power to take responsibility for their mental health and to seek help when needed.

Additionally, previous studies found personal growth to be correlated with psychological well-being (Sharma & Rani, 2014). In the current study, personal growth belongs to the domain of psychological well-being but is correlated with the other symptoms within that domain. Nevertheless, Sharma and Rani's (2014) results indicate that increasing personal growth can improve other aspects of psychological well-being as well. Personal growth could be applied to a range of life domains, including relationships, personality, or career. That personal growth is this multifaceted could be a reason why it is so strongly associated with other domains of the network.

Further, mastery and personal growth both belong to the domain psychological well-being, which de Vos et al. (2021) found as the most important domain in their domain network. In the current study, psychological well-being is the most important of the three well-being nodes, but not the most important in the entire network. The reason that psychological well-being is the most important well-being domain in these mental health networks, could also be that the other cluster (psychological distress) also focuses on the psychological aspects. The distress cluster does not explicitly measure social distress or emotional distress, which could be the corresponding domains to the well-being cluster. Certainly, social and emotional aspects play a role in the psychological distress cluster as well, but perhaps not as dominantly as the psychological aspects. Because of this, psychological well-being may have stronger connections to the psychological distress cluster and may be therefore more relevant for the entire network.

Emotional well-being and depression were the domains with the highest bridge centrality in the network on the domain level, which indicates that these domains connect the two clusters. In the network on domain and symptom level, depression and paranoid ideation are important domains that connect both clusters. The strong correlations of depression within the own cluster of psychological distress, but also to the other cluster of well-being, once again highlights its importance in treatment.

No differences in the overall network structure or global strength of the network could be found between male and female participants. Regarding prevalence, in clinical samples, women are more often affected by mental illness than men (Steel et al., 2014). Although the current study did not research a clinical sample but one that represents the general population, a similar trend was expected, as psychological distress in this study was measured with the Brief Symptom Inventory (BSI) which provides an overview of a person's mental illness-related symptoms (Derogatis, 2001). The current study found that women score higher than men in severity for the domains somatization, interpersonal sensitivity, anxiety, and phobic anxiety. However, in network analysis, no conclusions are drawn regarding severity or prevalence, but about how different domains are correlated. In this aspect, the networks do not differ between genders. Consequently, the difference between genders might be restricted to prevalence and severity of psychological distress and well-being, but do not show in the structure of the mental health network. Perhaps, this is the case because of the stigma around mental health, especially for men. Generally, the prevalence of mental illnesses is lower for men, but it is often overlooked (Chatmon, 2020). This could be an indicator that the differences, in reality, are not as big as they seem, as men are not as willing to indicate that they suffer from a mental illness as women are. Possibly, this leads to a biased perception of differences between men and women in mental health. The structure of mental health may not be as easy to manipulate in questionnaires as prevalence or severity, which could be why no difference was found here between genders.

Between the networks of married and not married participants, no difference in overall network structure was found either. However, a difference in global strength could be established. Social well-being and psychoticism had higher strength centralities (i.e. stronger connections within the network) and might therefore be more important for the entire network for not married participants than for married participants. It could be hypothesised that social well-being is more robust for married individuals, meaning that it is less affected by other mental health domains. Perhaps, the relationship with the spouse can be understood as a major part of the person's social well-being and gives a feeling of security. Because of this sense of a stable relationship, the overall social well-being may be less prone to other stressors and therefore relatively independent of how other domains in the mental health network change. Psychoticism on the other hand includes antisocial behaviour, aggression, and aloofness (Sam, 2013). These facets may make it more difficult to sustain a stable relationship, which could be a reason why scores on psychoticism are higher for people who are not married in this sample. Further, dealing with the symptoms of psychoticism is already challenging, and without the stableness and security a marriage entails, these challenges could become even more difficult and therefore more important for overall mental health.

Regarding the severity of psychological distress and well-being in married versus not married people, the current study is in line with previous research which showed that the mental health of married people is better (Wilson & Oswald, 2005). In the current study, married people scored higher in emotional well-being, and lower in obsession-compulsion, depression, anxiety, phobic anxiety, paranoid ideation and psychoticism. However, it is important to note that the categories of married and not married are very broad. For example, happy relationships which are not marriages, are also beneficial for mental health (CBS, 2021), and being married is not equal to being in a happy relationship. Consequently, variations within the groups married and not married are likely to be large. Lastly, the network of not married participants only included half the number of participants as the network for married people, which might be the reason for the weaker stability of this network.

Theoretical Contributions and Implications

The current study is the first that computed a psychometric network structure of the general population while including a wide range of psychological stress and well-being domains, which therefore lead to new insights. The network on the domain level and the network on the domain and symptom level are similar in many aspects, and it became evident that the domains/symptoms within one cluster are more strongly connected with each other than domains/symptoms between clusters. This implies that different domains of psychological distress are related to each other, and the same is the case for well-being. Accordingly, changes in one part of the network can become apparent in the rest of the cluster, and even in the other cluster. In other words, if one domain increases in severeness, other domains are at risk to increase as well, and the other way around. As the analysis showed, depression is the most important domain, meaning it has the strongest associations with other domains in the network. This could indicate that it has the strongest influence on the rest of the mental health network, and/or that it is influenced by several other domains in the network. Anxiety, mastery, and personal growth are also critical nodes with great associations with the others. This knowledge could be used in treatment or prevention interventions. Targeting these most important domains may change other domains in the entire network (Borsboom, 2017), which is a lot more efficient than targeting every single domain separately. For example, targeting depression could also improve psychoticism, anxiety, and emotional well-being. However, remains an assumption and further research is needed to test this, for example in longitudinal studies that target specific domains.

The results of this study indicate that it is crucial to target both, psychological distress and well-being domains in interventions, to ensure the best possible impact. Currently, there are different interventions available for the general population. For example, e-health interventions have shown to be effective in preventing depression and anxiety (Deady et al., 2017). Personal growth is also promoted in e-health interventions (East & Havard, 2015). These kinds of interventions are easily accessible to a wide range of individuals and therefore ideal for reaching a lot of people. Especially people who are at-risk to develop a pathological illness, but do not seek help from a therapist yet, can be helped early on before a serious mental illness develops. Another example of interventions that reduce anxiety and depression symptoms, while increasing satisfaction in life (which is a symptom of emotional well-being), are mindfulness-based interventions (Shankland et al., 2021). Research shows that associations between mindfulness and mental health are present in the general population (Burzler et al., 2019), which supports the idea of mindfulness training as a mental health promoting intervention for this group. Lastly, mastery could be increased in a study by Bélanger et al. (2019), in a 1-week intervention. Participants increased their environmental mastery by using if-then plans to achieve their goals (Bélanger et al., 2019). In all cases, effects on other than the targeted parts of the mental health network need to be investigated in the future.

Strengths and Limitations

The most apparent strength of this study is, that the network includes a broad range of aspects of mental health. This has the advantage that the risk to overlook important aspects is smaller, for example, relationships between domains and symptoms are investigated which otherwise would not have been researched individually. Next, different facets of well-being are included, as well as a range of different psychological distress domains. This is a unique feature of this study, as previous research often only focused on one aspect of well-being, or specific mental disorders. Further, the network was estimated on both the domain level and the domain and symptom level. Both have their own advantages and disadvantages, like the network on the domain level is less complex and therefore easier to interpret. However, in this network, the focus is naturally more on the psychological distress cluster, as it consists of more domains. The possibility of detailed insights into the well-being cluster is therefore limited. The network that includes well-being on a symptom level, solves this issue. The network increases in complexity and allows for a more detailed understanding of the mental health network. Overall, being able to investigate both networks enables a more holistic view of mental health.

However, computing these two networks also poses challenges. By including symptoms for one cluster, and domains for the other, interpretations must be made with caution. Symptoms describe a condition more specific than a domain, so there can be variations within one domain. Another limitation of this study is, that no matter how complex the network structure is, it will never display a completely realistic picture of mental health. Given the complicated nature of mental health, it is impossible to include every factor that influences it. Therefore, this network analysis can only display a fragment of reality.

Further, this study is a cross-sectional study design which means only limited conclusions can be drawn regarding effects and causality. Only correlations can be detected, but it is unclear whether the correlation exists in both directions or only one. Assumptions about influences of domains or symptoms on the network can be drawn from that, but they remain assumptions and cannot be validated based on the cross-sectional data. For example, we know that depression and anxiety are correlated, but it is not clear if one influences the other (or both), or if both domains are influenced by other factors. As all data was collected at one point in time, it is not possible to analyse how the networks develop over time and if change in one node predicts change in another node. Experience sampling studies could be used to validate these assumptions and show how networks develop over time. Currently, only a few network analyses that used experience sampling are available. One of them was conducted by Faelens et al. (2021), who researched the relationship between social media use and well-being. They found that social media use predicts reduced well-being, with social comparison, self-esteem, and repetitive negative thinking as important intermediate constructs in this relationship (Fealens et al., 2021). Another study researched the emotional dynamics of bipolar disorder at the symptom level of a single patient, and estimated networks of the hypomanic state, and the depressive state (Voigt et al., 2018). These studies highlight the value of using experience sampling, as it is possible to draw conclusions about effects and causality better. However, network studies about overall mental health that use experience sampling are still missing in the literature. Lastly, it is impossible to include every factor that has an influence on mental health in the analysis. Therefore, results cannot be generalized to the entire population, as even a large sample cannot reflect every aspect of reality.

Another limitation is the degree to which centrality can be used as a valuable indicator of the importance of a node. Snippe et al. (2017) propose another interesting perspective on the value of centrality. They conclude from their research, that mental states (i.e. symptoms) can change independently from their connection to each other. This does not exclude that there is no influence between symptoms, but it means that one symptom/domain can change without necessarily changing the others connected to it. As a consequence, the remaining symptoms/domains could again influence the one that changed, so that this change could reverse itself. This indicates, that targeting only one symptom or domain in the network might not be sufficient if the others remain untreated, as the targeted symptom/domain may be influenced by the others again, and so the progress may be undone. Therefore, it may be important to not only focus on the single most central symptom/domain in the network but to target other highly central symptoms as well, to achieve a sustaining effect. The results of Elliot et al. (2020) support this approach, as they found that targeting the most central symptoms during treatment leads to higher success.

Next, in this study, psychological distress was measured and treated as a milder form of mental illness. Conclusions were drawn about the two continua model, which consists of the two clusters psychopathology (mental illness), and well-being. However, Payton (2009) argues that despite their similarities, mental disorder and distress should be studied separately, and not be mixed up. They are not part of one continuum, but distinct phenomena. Consequently, the results of this study can only be applied to the two continua model with caution. On the other hand, the current study was done with a sample that represents the general Dutch population, and not a clinical sample. Measuring psychopathology in them would most likely not lead to results that are multifaceted enough, to lead to meaningful conclusions.

Lastly, as the data was collected with self-report questionnaires, the results may be biased. Reasons can be social desirability (Anglim et al., 2017), or the stigma around mental health problems.

Future Research

Future research should continue investigating mental health networks, to further improve understanding of overall mental health. This is crucial for being able to improve mental health in the general population. One option is, to create more equal clusters. For example, psychological distress and well-being could both be represented by symptoms, instead of domains or a combination of both. Through this, the network becomes more detailed and interactions between the symptoms can be investigated to a greater extent. This can help to develop more specific interventions.

Additionally, it is valuable to investigate how the mental health network changes over time, by using experience sampling. This will make it possible to draw more reliable conclusions about the effects the domains and symptoms have on each other.

Another important aspect to be studied in future research is to test the value of centrality in practice. Currently, it is assumed that the most central symptoms need to be targeted, to achieve change in the overall network. However, this is just an assumption and needs to be determined in practice. For this, mental health interventions which target depression, anxiety, mastery, and personal growth (the most important aspects of the mental health network) need to be examined regarding their effect on the entire mental health network. An experience sampling study design could be used to investigate changes in networks over time. Data of the general population could be collected before and after an intervention that targets the most central domains, and could then be analysed with psychometric data analysis. By this, the effects of such interventions on the entire network could be investigated.

Conclusion

This study leads to new insights into the structure of mental health in the general population. Mental health networks were estimated, which included psychological distress, as well as well-being. Until now, these kinds of networks were only estimated for clinical populations or specific aspects of mental health. Two different networks were calculated for the entire sample, one on domain level and the other one on domain level for the psychological distress cluster, and on symptom level for the well-being cluster. Results revealed that depression and anxiety were the most important domains in the first network, and depression, mastery, and personal growth in the latter network. Consequently, these should be targeted in mental health interventions. In both, the network on the domain level, and the network on the domain/symptom level, a clear distinction between the two clusters (psychological distress and well-being) is observable, despite some connections between the two clusters. This finding confirms the two continua model (Keyes, 2002, 2005). In the network on domain and symptom level, the two clusters were more balanced in terms of centrality, which indicates that they might be equally important for overall mental health. No differences could be found in the network structure between men and women, which indicates that interventions can be developed independently of gender. However, as differences in global strength between participants who are married and those who are not were found (social well-being and psychoticism seem to be more relevant for people who are not married), it will be important to take life circumstances into account when choosing or developing an appropriate intervention. In all networks, a clear distinction between the two clusters became apparent. This supports the two continua model, as it shows that psychological distress and well-being are separate constructs, yet they are correlated. These findings broaden the understanding of mental health and can contribute to the development of effective interventions for improving mental health.

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Appendix

Appendix A: Tables and Figures

Table A1

Edge Weights (Partial Correlations) of the Entire Sample

From	To	Weight/correlation (*r*)
Emotional Well-being	Social Well-being	.15
Emotional Well-being	Psychological Well-being	.38
Social Well-being	Psychological Well-being	.49
Somatization	Obsession-Compulsion	.13
Obsession-Compulsion	Interpersonal Sensitivity	.1
Emotional Well-being	Depression	-.22
Obsession-Compulsion	Depression	.12
Interpersonal Sensitivity	Depression	.14
Somatization	Anxiety	.24
Obsession-Compulsion	Anxiety	.17
Depression	Anxiety	.25
Obsession-Compulsion	Hostility	.1
Interpersonal Sensitivity	Hostility	.13
Anxiety	Hostility	.14
Somatization	Phobic Anxiety	.12
Obsession-Compulsion	Phobic Anxiety	.07
Interpersonal Sensitivity	Phobic Anxiety	.18
Depression	Phobic Anxiety	.07
Anxiety	Phobic Anxiety	.22
Obsession-Compulsion	Paranoid Ideation	.09
Interpersonal Sensitivity	Paranoid Ideation	.28
Depression	Paranoid Ideation	.11
Anxiety	Paranoid Ideation	.06
Hostility	Paranoid Ideation	.22
Emotional Well-being	Psychoticism	-.05
Obsession-Compulsion	Psychoticism	.08
Interpersonal Sensitivity	Psychoticism	.16
Depression	Psychoticism	.4
Anxiety	Psychoticism	.05
Phobic Anxiety	Psychoticism	.09
Paranoid Ideation	Psychoticism	.11

Table A2

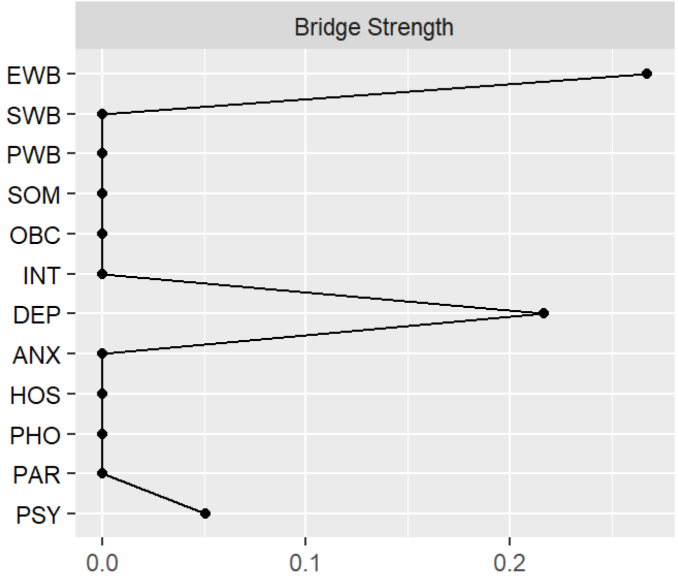
Node Strength Centrality Network of Entire Sample (Domain Level)

Node	*S*
Depression	1.99
Anxiety	1.22
Interpersonal Sensitivity	.58
Psychoticism	.38
Psychological Well-being	.11
Paranoid Ideation	.10
Obsession-Compulsion	-.01
Emotional Well-being	-.22
Phobic Anxiety	-.47
Social Well-being	-.88
Hostility	-1.18
Somatization	-1.62

Note. S = Strength Centrality (standardized values)

Figure A1

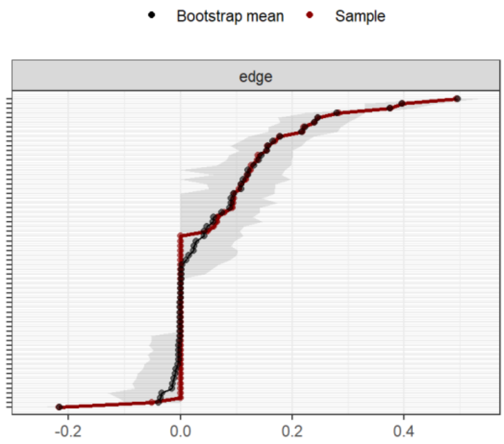
Bridge Centrality of the Entire Sample (Domain Level)



Note. SOM = Somatization, OBC = Obsession-Compulsion, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism, EWB = emotional well-being, PWB = psychological well-being, SWB = social well-being. The x-axis represents the scale of strength centralities.

Figure A2

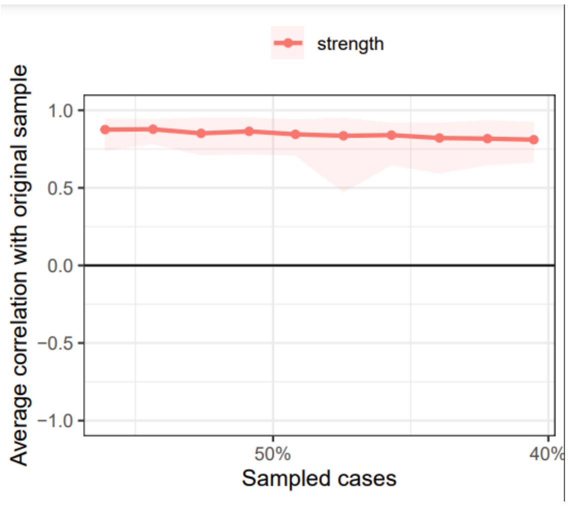
Edge-weight Accuracy of the Network of the Entire Sample (Domain Level)



Note. On the y-axis, the edges of the network are represented (ordered from highest to lowest edge-weight). The x-axis represents the scale of the edge weights. The red line represents the sample values, and the black line the mean of the bootstrapped edge strengths. The grey area represents the bootstrapped confidence intervals. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A3

Centrality Stability Plot of the Entire Sample (Domain Level)



Note. Stability of the strength centrality measures that shows average correlations between centrality measures in the original network with the centrality of sampled networks. In those sampled networks, participants are randomly dropped. The x-axis shows the percentage of participants the network is sampled with (after participants dropped out). High correlations with a high percentage of participants dropped, indicate stable centrality measures in the original sample.

Table A3

Edge-weights (Partial Correlations) of the Entire Sample (Symptom and Domain Level)

	HAP	IIL	LSA	CON	SIN	ACT	ACC	COH	SAC	MAS	POR	PGR	AUT	PIL	SOM	INT	DEP	ANX	HOS	PHO	PAR	PSY
HAP	0	.21	.39	.01	0	.09	0	.09	.05	.04	.16	0	.01	.11	0	0	.09	0	.02	0	0	.04
IIL		0	.21	.07	.04	.03	.07	.07	0	.09	.03	.01	.04	.13	0	0	0	0	0	.04	0	0
LSA			0	.08	0	0	0	0	0	.12	.04	.05	0	0	0	.05	.11	.04	.09	0	.05	0
CON				0	.3	.14	.04	0	.06	.03	.03	.09	0	.11	0	.03	.05	.06	.01	0	.07	0
SIN					0	.09	0	.03	0	.01	.11	.07	.04	.03	0	0	0	0	.03	0	.01	0
ACT						0	.29	.15	.08	.06	.07	.11	0	.02	0	0	0	0	0	.04	.01	.01
ACC							0	.19	.08	.04	.06	0	0	.04	.02	0	.05	.01	.05	0	.11	0
COH								0	.17	.09	.01	.1	.09	.05	.04	0	0	.01	.02	.03	0	.05
SAC									0	.30	.04	.09	.12	.09	0	.01	0	0	.02	0	.01	0
MAS										0	.16	.13	.09	.15	0	0	.01	.06	.08	0	.08	0
POR											0	.16	.14	.08	0	0	.05	.02	.02	0	.07	.06
PGR												0	.22	.13	.03	.06	.04	.04	0	.03	.01	.07
AUT													0	.22	.02	.11	0	0	.09	.03	0	0
PIL														0	.01	.04	.08	0	.01	0	.03	0
SOM															0	0	.06	.27	.06	.13	0	0
INT																0	.17	0	.17	.19	.29	.16
DEP																	0	.28	.02	.07	.13	.42
ANX																		0	.18	.25	.07	.06
HOS																			0	.06	.22	0
PHO																				0	0	.09
PAR																					0	.11
PSY																						0

Note. HAP = Happiness, ILL = Interest in Life, LSA = Life Satisfaction, CON = Social Contribution, SIN = Social Integration, ACT = Social Actualization, ACC = Social Acceptation, COH = Social Coherence, SAC = Self-Acceptance, MAS = Mastery, POR = Positive Relations, PGR = Personal Growth, AUT = Autonomy, PIL = Purpose in Life, SOM = Somatization, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism

Table A4

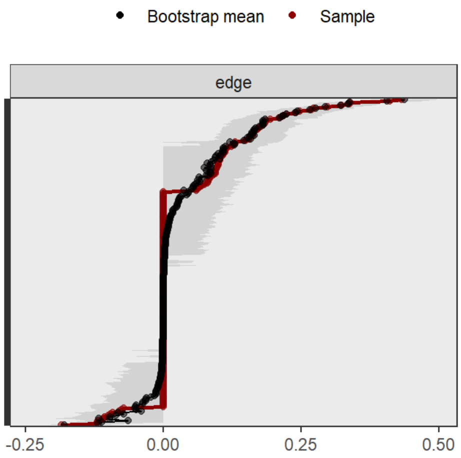
Node Strength Centrality Network of Entire Sample (Symptom and Domain Level)

Node	*S*
Happiness	.57
Interest In Life	-.61
Life Satisfaction	.13
Social Contribution	-.08
Social Integration	-1.89
Social Actualization	-.001
Social Acceptation	-.56
Social Coherence	.02
Self-Acceptance	-.32
Mastery	1.59
Positive Relations	.53
Personal Growth	1.09
Autonomy	.06
Purpose in Life	.59
Somatization	-2.47
Interpersonal Sensitivity	.36
Depression	1.86
Anxiety	.64
Hostility	-.26
Phobic Anxiety	-1.08
Paranoid Ideation	.44
Psychoticism	-.62

Note. *S* = Strength Centrality (standardized values)

Figure A4

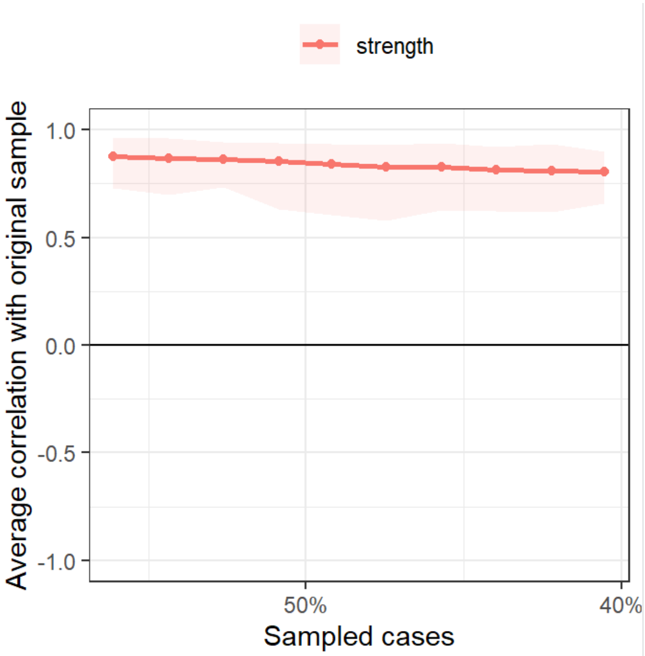
Edge-weight Accuracy of the Network of the Entire Sample (Symptom and Domain Level)



Note. On the y-axis, the edges of the network are represented (ordered from highest to lowest edge-weight). The x-axis represents the scale of the edge weights. The red line represents the sample values, and the black line the mean of the bootstrapped edge strengths. The grey area represents the bootstrapped confidence intervals. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A5

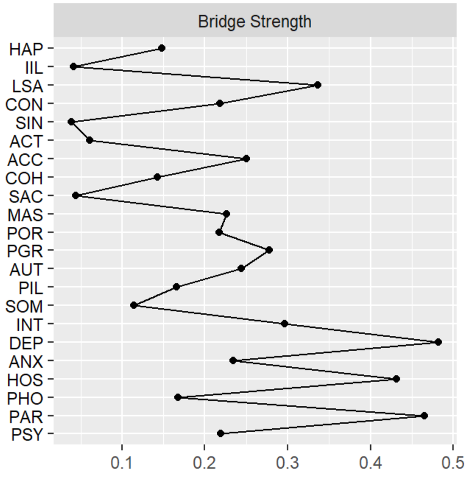
Centrality Stability Plot of the Network of Entire Sample (Symptom and Domain Level)



Note. Stability of the strength centrality measures that shows average correlations between centrality measures in the original network with the centrality of sampled networks. In those sampled networks, participants are randomly dropped. The x-axis shows the percentage of participants the network is sampled with (after participants dropped out). High correlations with a high percentage of participants dropped, indicate stable centrality measures in the original sample.

Figure A6

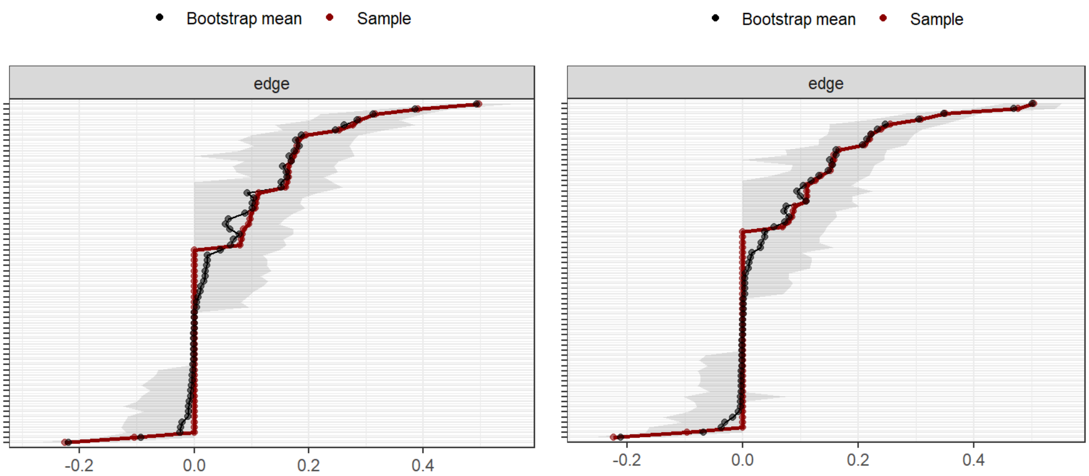
Bridge Centrality of the Entire Sample (Symptom and Domain Level)



Note. HAP = Happiness, ILL = Interest in Life, LSA = Life Satisfaction, CON = Social Contribution, SIN = Social Integration, ACT = Social Actualization, ACC = Social Acceptation, COH = Social Coherence, SAC = Self-Acceptance, MAS = Mastery, POR = Positive Relations, PGR = Personal Growth, AUT = Autonomy, PIL = Purpose in Life, SOM = Somatization, INT = Interpersonal Sensitivity, DEP = Depression, ANX = Anxiety, HOS = Hostility, PHO = Phobic Anxiety, PAR = Paranoid Ideation, PSY = Psychoticism. The x-axis represents the scale of strength centralities.

Figure A7

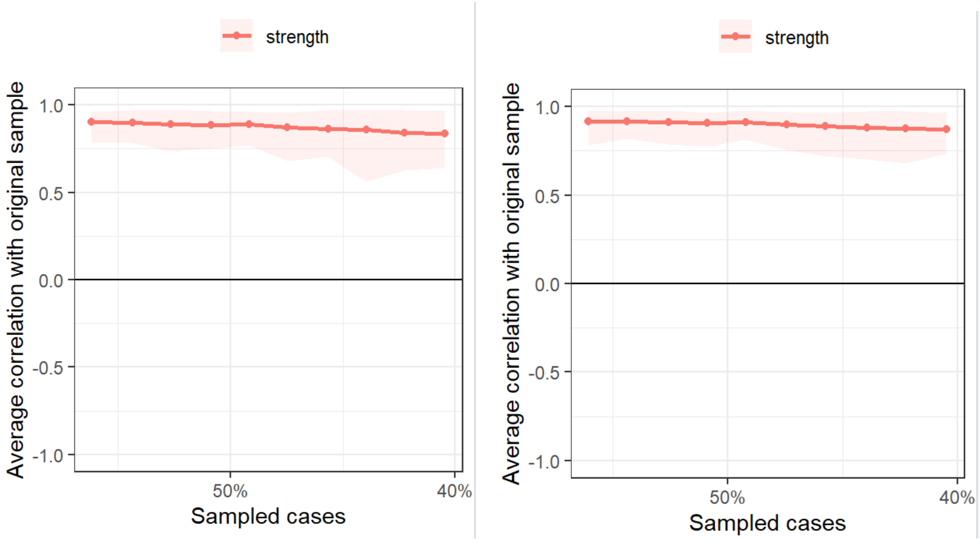
Edge-weight Accuracy of the Network of the Male (Left) and Female (Right) Participants



Note. On the y-axes, the edges of the networks are represented (ordered from highest to lowest edge-weight). The x-axes represent the scale of the edge weights. The red lines represent the sample values, and the black lines the means of the bootstrapped edge strengths. The grey areas represents the bootstrapped confidence intervals. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A8

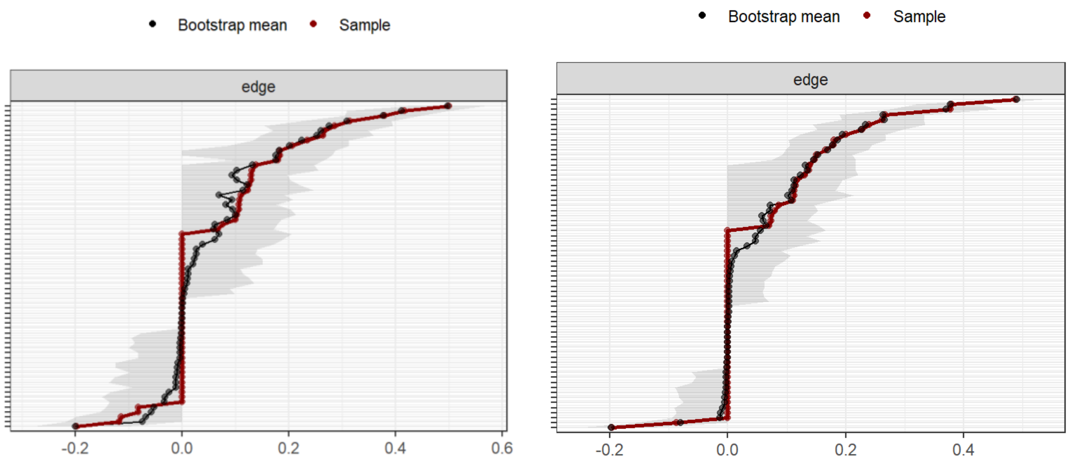
Centrality Stability Plot of Male (Left) and Female (Right) Participants



Note. Stability of the strength centrality measures that shows average correlations between centrality measures in the original networks with the centrality of sampled networks. In those sampled networks, participants are randomly dropped. The x-axes show the percentage of participants the network is sampled with (after participants dropped out). High correlations with a high percentage of participants dropped, indicate stable centrality measures in the original sample.

Figure A9

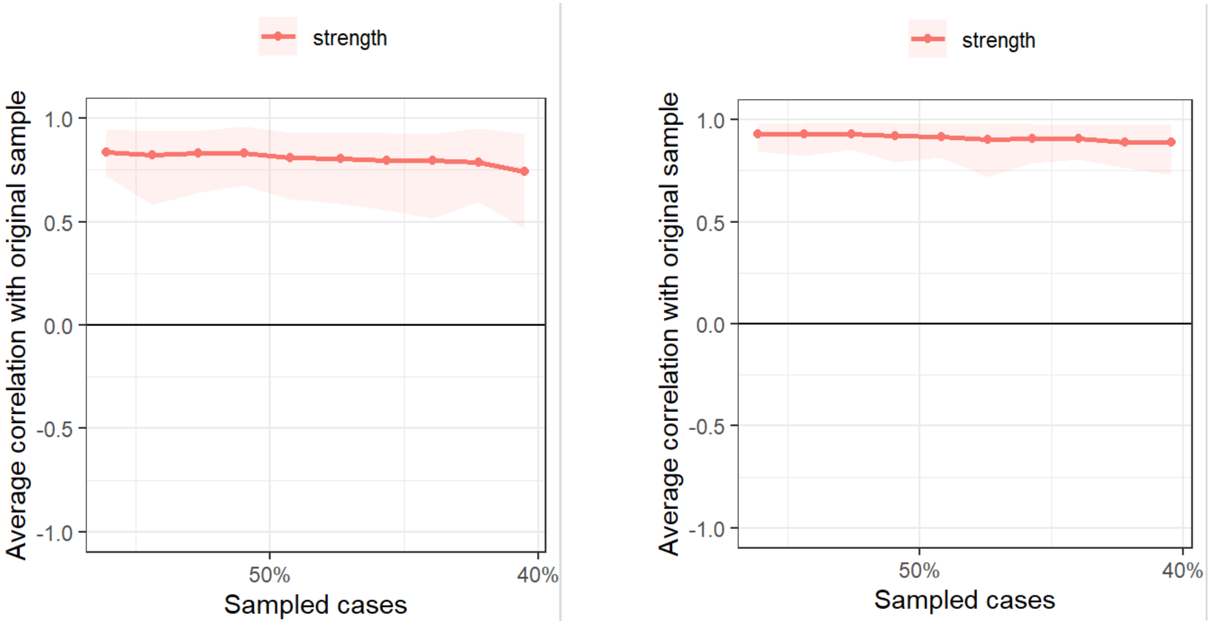
Edge-weight Accuracy of the Network of the Not Married (Left) and Married (Right) Participants



Note. On the y-axes, the edges of the networks are represented (ordered from highest to lowest edge-weight). The x-axes represent the scale of the edge weights. The red lines represent the sample values, and the black lines the means of the bootstrapped edge strengths. The grey areas represents the bootstrapped confidence intervals. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A10

Centrality Stability Plot of not Married (Left) and Married (Right) Participants



Note. Stability of the strength centrality measures that shows average correlations between centrality measures in the original networks with the centrality of sampled networks. In those sampled networks, participants are randomly dropped. The x-axes show the percentage of participants the network is sampled with (after participants dropped out). High correlations with a high percentage of participants dropped, indicate stable centrality measures in the original sample.

Table A5

Node Strength Centralities of Male and Female Participants

Node	Male	Female	p
Emotional Well-being	-.01	-.04	.55
Social Well-being	-.57	-.75	.25
Psychological Well-being	.44	.08	.20
Somatization	-1.95	-1.18	.55
Obsession-Compulsion	-.11	-.55	.25
Interpersonal Sensitivity	.56	.81	.90
Depression	1.57	2.51	.05
Anxiety	1.26	.70	.05
Hostility	-.99	-.94	.75
Phobic Anxiety	-.98	-.54	.75
Paranoid Ideation	.20	.16	.75
Psychoticism	.56	-.26	.10

Note. Standardized Strength Centralities for the subgroups. The p-value indicates whether a significant difference between the groups could be found.

Table A6

Node Strength Centralities of Married and not Married Participants

Node	married	not married	p
Emotional Well-being	-.02	-.33	.80
Social Well-being	-.81	.77	.00
Psychological Well-being	.23	.24	.25
Somatization	-1.36	-2.26	.10
Obsession-Compulsion	-.21	-1.12	.40
Interpersonal Sensitivity	.85	-.22	.10
Depression	2.24	1.23	.60
Anxiety	.98	1.22	.15
Hostility	-.69	-.24	.25
Phobic Anxiety	-1.03	-.14	.15
Paranoid Ideation	.14	-.04	.80
Psychoticism	-.34	.89	.00

Note. Standardized Strength Centralities for the subgroups. The p-value indicates whether a significant difference between the groups could be found.

Appendix B: R Code

```
#load packages

library(psych)

library(summarytools)

library(haven)

library(qgraph)

library(bootnet)

library(NetworkComparisonTest)

library(networktools)

library(mgm)

library(devtools)


#calculate cronbachs alpha for the questionnaires:

MHCdata <- basis_MESS_december2007[50:63]

alpha(MHCdata)


MHCemotional <- MHCdata[1:3]

alpha(MHCemotional)


MHCsocial <- MHCdata[4:8]

alpha(MHCsocial)


MHCpsychological <- MHCdata[9:14]

alpha(MHCpsychological)
```

```
# exclude unnecessary variables

excl_vars <- names(basis_MESS_december2007[c(1:10,12,13,15:18,20:49,78:96)])

tidydataset <-

basis_MESS_december2007[,!(names(basis_MESS_december2007)%in%excl_vars)]


#change variable names

colnames(tidydataset)[colnames(tidydataset)=="MHChed"] <- "EWB"

colnames(tidydataset)[colnames(tidydataset)=="MHCpsy"] <- "PWB"

colnames(tidydataset)[colnames(tidydataset)=="MHCsoc"] <- "SWB"

colnames(tidydataset)[colnames(tidydataset)=="MHC01"] <- "HAP"

colnames(tidydataset)[colnames(tidydataset)=="MHC02"] <- "IIL"

colnames(tidydataset)[colnames(tidydataset)=="MHC03"] <- "LSA"

colnames(tidydataset)[colnames(tidydataset)=="MHC04"] <- "CON"

colnames(tidydataset)[colnames(tidydataset)=="MHC05"] <- "SIN"

colnames(tidydataset)[colnames(tidydataset)=="MHC06"] <- "ACT"

colnames(tidydataset)[colnames(tidydataset)=="MHC07"] <- "ACC"

colnames(tidydataset)[colnames(tidydataset)=="MHC08"] <- "COH"

colnames(tidydataset)[colnames(tidydataset)=="MHC09"] <- "SAC"

colnames(tidydataset)[colnames(tidydataset)=="MHC10"] <- "MAS"

colnames(tidydataset)[colnames(tidydataset)=="MHC11"] <- "POR"

colnames(tidydataset)[colnames(tidydataset)=="MHC12"] <- "PGR"

colnames(tidydataset)[colnames(tidydataset)=="MHC13"] <- "AUT"

colnames(tidydataset)[colnames(tidydataset)=="MHC14"] <- "PIL"

colnames(tidydataset)[colnames(tidydataset)=="BSISOM"] <- "SOM"

colnames(tidydataset)[colnames(tidydataset)=="BSICOG"] <- "OBC"
```

```
colnames(tidydataset)[colnames(tidydataset)=="BSIINT"] <- "INT"
colnames(tidydataset)[colnames(tidydataset)=="BSIDEP"] <- "DEP"
colnames(tidydataset)[colnames(tidydataset)=="BSIANG"] <- "ANX"
colnames(tidydataset)[colnames(tidydataset)=="BSIHOS"] <- "HOS"
colnames(tidydataset)[colnames(tidydataset)=="BSIFOB"] <- "PHO"
colnames(tidydataset)[colnames(tidydataset)=="BSIPAR"] <- "PAR"
colnames(tidydataset)[colnames(tidydataset)=="BSIPSY"] <- "PSY"

#see summary of the data (includes descriptives for participants)
View(dfSummary(tidydataset))

#exclude all variables that are not MHC or BSI domains
excl_demog <- names(tidydataset[c(1:18,22)])
domainsdataset <- tidydataset[,!(names(tidydataset)%in%excl_demog)]

#exclude all variables that are not BSI domains or MHC items
excl_sym <- names(tidydataset[c(1:3, 18:22)])
symptomsdataset <- tidydataset[,!(names(tidydataset)%in%excl_sym)]

#goldbricker function to identify redundant nodes
goldbricker(domainsdataset, p = 0.01, method = "hittner2003", threshold = 0.25,
        corMin = 0.5, progressbar = TRUE)

goldbricker(symptomsdataset, p = 0.01, method = "hittner2003", threshold = 0.25,
        corMin = 0.5, progressbar = TRUE)
```

```
#exclude redundant variables/nodes
excl_gold <- names(symptomsdataset[c(16)])
symptomsdataset <- symptomsdataset[,!(names(symptomsdataset)%in%excl_gold)]

#create subsample male participants
malepart <- tidydataset
malepart <- subset(malepart, geslacht==1)
excl_male <- names(malepart[c(1:18,22)])
malepart <- malepart[,!(names(malepart)%in%excl_male)]

#create subsample female participants
femalepart <- tidydataset
femalepart <- subset(femalepart, geslacht==2)
excl_female <- names(femalepart[c(1:18,22)])
femalepart <- femalepart[,!(names(femalepart)%in%excl_female)]

#create subsample not married participants
singlepart <- tidydataset
singlepart <- subset(singlepart, partner==0)
excl_single <- names(singlepart[c(1:18,22)])
singlepart <- singlepart[,!(names(singlepart)%in%excl_single)]

#create subsample married participants
marriedpart <- tidydataset
```

```
marriedpart <- subset(marriedpart, partner==1)
excl_married <- names(marriedpart[c(1:18,22)])
marriedpart <- marriedpart[,!(names(marriedpart)%in%excl_married)]

#form the groups MHC and BSI (domain level)
group <- list(c(1:3), c(4:12))
names(group)=c(“Well-being”,”Psychological Distress”)

#form the groups MHC and BSI (symptom level)
groupsym <- list(c(1:3), c(4:8), c(9:14), c(15:22))
names(groupsym)=c("Emotional Well-being", "Social Well-being", "Psychological Well-being","Psychological Distress")

#compare means of the subsamples (t-test)
t.test(malepart$EWB, femalepart$EWB, alternative = "two.sided", var.equal = TRUE)
t.test(malepart$SWB, femalepart$SWB, alternative = “two.sided”, var.equal = TRUE)
…
t.test(singlepart$EWB, marriedpart$EWB, alternative = "two.sided", var.equal = TRUE)
….

#estimate network of well-being and psychological distress, for the entire sample (domain level)
set.seed(1)
```

everyone_network <- qgraph(input = cor_auto(domainsdataset), groups=group, layout = “spring”, graph = "EBICglasso", legend = TRUE, sampleSize = nrow(domainsdataset), threshold = TRUE, filetype = ".png", esize = 11, color=c("yellow", "turquoise"))

Layout <- averageLayout(everyone_network)

#calculate partial correlations for the domain network

myedges <- getWmat(everyone_network)

#estimate network on symptom level (Well-being) and domain level (psychological distress)

data <- symptomsdataset

data <- na.omit(data)

data <- as.matrix(data)

p <- ncol(data)

dim(data)

set.seed(1)

fit.symptoms <- mgm (data=data,

type = rep('g',p),

level = rep(1,p),

lambdaSel = 'CV',

ruleReg = 'OR',

pbar = FALSE)

symptoms_network <- qgraph(fit.symptoms$pairwise$wadj,

groups = groupsym,

layout = "spring",

```
        legend = TRUE,
    filetype = ".png",
    esize = 11,
    color=c("gold", "lightyellow", "yellow", "turquoise"),
    edge.color = fit.symptoms$pairwise$edgecolor,
    labels = colnames(data))

#calculate partial correlations for the symptom network
symedges <- getWmat(symptoms_network)

#estimate network of well-being and psychological distress, for males
set.seed(1)
male_network <- qgraph(input = cor_auto(malepart), groups=group, layout = Layout, graph
= "EBICglasso", legend = FALSE, sampleSize = nrow(malepart), threshold = TRUE, filetype
= ".png", esize = 11, color=c("yellow", "turquoise"))

#estimate network of well-being and psychological distress, for females
set.seed(1)
female_network <- qgraph(input = cor_auto(femalepart), groups=group, layout = Layout,
graph = "EBICglasso", legend = TRUE, sampleSize = nrow(femalepart), threshold = TRUE,
filetype = ".png", esize = 11, color=c("yellow", "turquoise"))

#estimate network of well-being and psychological distress, for not married participants
set.seed(1)
```

```
single_network <- qgraph(input = cor_auto(singlepart), groups=group, layout = Layout,
graph = "EBICglasso", legend = FALSE, sampleSize = nrow(singlepart), threshold = TRUE,
filetype = ".png", esize = 11, color=c("yellow", "turquoise"))

#estimate network of well-being and psychological distress, for married participants
set.seed(1)
married_network <- qgraph(input = cor_auto(marriedpart), groups=group, layout = Layout,
graph = "EBICglasso", legend = TRUE, sampleSize = nrow(marriedpart), threshold = TRUE,
filetype = ".png", esize = 11, color=c("yellow", "turquoise"))

#centrality estimates (incl. plots and tables) for each network
centralityPlot((everyone_network), include = "Strength", orderBy="Strength", scale = “z-
scores”)
centralityPlot((symptoms_network), include = "Strength", orderBy="Strength", scale = “z-
scores”)
centralityTable(everyone_network)
centralityTable(symptoms_network)
centralityTable(male_network)
centralityTable(female_network)
centralityTable(single_network)
centralityTable(married_network)

#centrality Plots of male/female, and married/not married participants
centralityPlot(list(“Male”=male_network, “Female”=female_network), include = "Strength",
orderBy = "Strength", scale = “z-scores”)
```

```
centralityPlot(list("Not Married"=single_network, "Married"=married_network), include =
"Strength", orderBy = "Strength", scale = "z-scores")

# calculate bridge centrality
mybridge <- bridge(everyone_network, communities=c('1', '1', '1', '2', '2', '2', '2', '2', '2', '2', '2',
'2'),useCommunities = 'all', directed = NULL, nodes = NULL)

#plot bridge centrality
plot(mybridge, include = "Bridge Strength")

# bridge centrality symptom level
symbridge <- bridge(symptoms_network, communities=c('1', '1', '1',
'1','1','1','1','1','1','1','1','1','1','1','1','2', '2', '2', '2', '2', '2', '2', '2'),useCommunities = 'all', directed =
NULL, nodes = NULL)

#plot bridge centrality (symptom level)
plot(symbridge, include = "Bridge Strength")

#stability analysis of the entire sample network (first edge-weight accuracy, then centrality
stability)
set.seed(123)
everyone_NW <-estimateNetwork(domainsdataset, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)

set.seed(123)
```

```
boot_everyone <- bootnet(everyone_NW, statistics = "edge", nBoots = 1000, nCores = 4)
plot(boot_everyone, labels = FALSE, order = "sample")
summary(boot_everyone)
print(boot_everyone)

set.seed(123)
boot_everyone2 <- bootnet(everyone_NW, statistics = "strength", nBoots = 1000, type =
"case", nCores = 4, caseMin = 0.439, caseMax = 0.595)
corStability(boot_everyone2, cor = 0.7, statistics = "strength", verbose = TRUE)
print(boot_everyone2)
plot(boot_everyone2)

#stability analysis of male participants (edge-weight accuracy and centrality stability)
set.seed(123)
male_NW <-estimateNetwork(malepart, corMethod = "cor_auto", default = "EBICglasso",
threshold = TRUE)

set.seed(123)
boot_male <- bootnet(male_NW, statistics = "edge", nBoots = 1000, nCores = 4)
plot(boot_male, labels = FALSE, order = "sample")
summary(boot_male)
print(boot_male)

set.seed(123)
```

```
boot_male2 <- bootnet(male_NW, statistics = "strength", nBoots = 1000, type = "case",
nCores = 4, caseMin = 0.439, caseMax = 0.595)
corStability(boot_male2, cor = 0.7, statistics = "strength", verbose = TRUE)
print(boot_male2)
plot(boot_male2)

#stability analysis of female participants (edge-weight accuracy and centrality stability)
set.seed(123)
female_NW <-estimateNetwork(femalepart, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)

set.seed(123)
boot_female <- bootnet(female_NW, statistics = "edge", nBoots = 1000, nCores = 4)
plot(boot_female, labels = FALSE, order = "sample")
summary(boot_female)
print(boot_female)

set.seed(123)
boot_female2 <- bootnet(female_NW, statistics = "strength", nBoots = 1000, type = "case",
nCores = 4, caseMin = 0.439, caseMax = 0.595)
corStability(boot_female2, cor = 0.7, statistics = "strength", verbose = TRUE)
print(boot_female2)
plot(boot_female2)

#stability analysis of not married participants (edge-weight accuracy and centrality stability)
```

```
set.seed(123)

single_NW <-estimateNetwork(singlepart, corMethod = "cor_auto", default = "EBICglasso",
threshold = TRUE)

set.seed(123)

boot_single <- bootnet(single_NW, statistics = "edge", nBoots = 1000, nCores = 4)

plot(boot_single, labels = FALSE, order = "sample")

summary(boot_single)

print(boot_single)

set.seed(123)

boot_single2 <- bootnet(single_NW, statistics = "strength", nBoots = 1000, type = "case",
nCores = 4, caseMin = 0.439, caseMax = 0.595)

corStability(boot_single2, cor = 0.7, statistics = "strength", verbose = TRUE)

print(boot_single2)

plot(boot_single2)

#stability analysis of married participants (edge-weight accuracy and centrality stability)

set.seed(123)

married_NW <-estimateNetwork(singlepart, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)

set.seed(123)

boot_married <- bootnet(married_NW, statistics = "edge", nBoots = 1000, nCores = 4)

plot(boot_married, labels = FALSE, order = "sample")
```

```
summary(boot_married)
print(boot_married)

set.seed(123)
boot_married2 <- bootnet(married_NW, statistics = "strength", nBoots = 1000, type = "case",
nCores = 4, caseMin = 0.439, caseMax = 0.595)
corStability(boot_married2, cor = 0.7, statistics = "strength", verbose = TRUE)
print(boot_married2)
plot(boot_married2)

#stability of symptom network (edge-weight accuracy and centrality stability)
set.seed(123)
symptom_NW <-estimateNetwork(symptomsdataset, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)

set.seed(123)
boot_symptom <- bootnet(symptom_NW, statistics = "edge", nBoots = 1000, nCores = 4)
plot(boot_symptom, labels = FALSE, order = "sample")
summary(boot_symptom)
print(boot_symptom)

set.seed(123)
boot_symptom2 <- bootnet(symptom_NW, statistics = "strength", nBoots = 1000, type =
"case", nCores = 4, caseMin = 0.439, caseMax = 0.595)
corStability(boot_everyone2, cor = 0.7, statistics = "strength", verbose = TRUE)
```

```
print(boot_symptom2)
plot(boot_symptom2)

#compare networks of the different groups (gender and marital status)
set.seed(123)
malefemale <- NetworkComparisonTest::NCT(male_NW, female_NW, it = 20, binary.data =
FALSE, paired = FALSE, test.edges = TRUE, edges = "all", progressbar = TRUE,
test.centrality = TRUE, centrality = "strength", nodes = "all")
summary(malefemale)
print(malefemale)

set.seed(123)
singlemarried <- NetworkComparisonTest::NCT(married_NW, single_NW, it = 20,
binary.data = FALSE, paired = FALSE, test.edges = TRUE, edges = "all", progressbar =
TRUE, test.centrality = TRUE, centrality = "strength", nodes = "all")

summary(singlemarried)
print(singlemarried)
```