

Explorative Network Analysis of Well-being Structure in Dutch Population:

**Does Gender and Income have an Effect on Well-being
Structure?**

Ortiga Hasan

Department of Behavioural and Social Sciences, University of Twente

MSc Positive Clinical Psychology and Technology

Alejandro Dominguez Rodriguez (1st Supervisor)

Erik Taal (2nd Supervisor)

Date: 14th July 2023

Table of Contents

Abstract.....	4
Introduction	5
Theory of Well-being.....	5
Psychometric Network Analysis in Well-being Research.....	8
Differences of Well-being based on Gender.....	10
Differences of Well-being based on Income	11
The Current Study.....	12
Methods	13
Participants and Procedures	13
Measures	13
Data Analyses	15
Results	17
Network Structure in the General Dutch Population	17
Differences in Network Structure based on Gender	20
Differences in Network Structure based on Income	22
Discussion.....	26
Meaning of Gender for Well-being	30
Meaning of Income for Well-being	31
Theoretical Contributions and Implications.....	32
Strengths and Limitations	33
Future Research	36

Conclusion	37
References	38
Appendix	50
Appendix A: Tables and Figures	51
Appendix B: R Code.....	63

Abstract

Well-being has come into stronger focus with the advent of positive psychology. While many theories examine well-being and plenty is already known about it, there is not enough information to provide a comprehensive well-being framework that spans the construct of well-being in its entirety.

A psychometric network analysis (NA), allows identifying node strength centrality, including the most central facets/items of well-being and those that are considered to have the strongest influence on the overall network. Performing a NA, this study used data from an internet Dutch panel for longitudinal studies (N = 1662, aged 18 to 87 years mean=47.61, SD=17.74) to assess well-being with the Mental Health Continuum-Short Form questionnaire (MHC-SF).

The results of the NA showed node strength centrality for the overall network, for female and male group and for low- and middle income group. Furthermore, the networks of gender groups were compared with each other, and income groups were compared with each other for differences in the network structure of well-being.

In all networks, happiness was found to be the most central node. In addition, mastery was discovered as another central node in the networks for the entire sample, the male group and the middle-income group. No differences in the overall well-being structure were discovered within gender groups and within income groups. Hence, specific single differences between individual facets were found in the gender and income groups.

The results are consistent with previous studies. Further, the study expands the understanding of well-being structure in the general Dutch population. The results can be used as a basis for further well-being research.

Keywords: well-being, network analysis, strength centrality, Dutch population, MHC-SF.

Introduction

Theory of Well-being

The importance of well-being is shown by the fact that even the ancient philosophers dealt with the subject (Lambert et al., 2015). However, there is no consensus around a single psychological definition of well-being, but there is general agreement that at minimum, well-being includes the presence of positive emotions and moods, the absence of negative emotions, satisfaction with life, fulfillment and positive functioning (Andrews & Withey, 2012; Diener, 2000; Ryff & Keyes, 1995; Ryff, 2014). Nevertheless, despite the long scientific debate on the concept of well-being, the question arises as to why there has been no consensus on a unitary definition of well-being and what exactly are the determinants associated with well-being. What is more, well-being is one of the main factors when it comes to mental health according to the definition of the WHO (World Health Organization, 2022). Keyes's concept of well-being with the three domains emotional well-being (EWB), psychological well-being (PWB) and social well-being (SWB) cover the main elements mentioned in the WHO's definition of mental health (Westerhof & Keyes, 2010).

Contemporary theories of well-being typically focused on one philosophical tradition, either the hedonistic or the eudaimonistic approach (van de Weijer et al., 2021). Keyes combines both approaches in his concept of well-being, merging Diener's hedonistic theory on subjective well-being and Ryff's eudaimonic psychological well-being concept as well as his own concept of social well-being (eudaimonic approach) (Keyes, 1998; Lamers et al., 2011; Westerhof & Keyes, 2010).

Diener's theory on subjective well-being (also described as emotional well-being) is about achieving the highest possible pleasure and includes three facets: *feelings of happiness, satisfaction and interest in life* (Diener, 1984; Keyes, 2007). Ryff's eudaimonic

definition of well-being, which has the focus on optimal functioning in individual and social life, is the concept of psychological well-being and has six facets: *autonomy, environmental mastery, personal growth, positive relationships, purpose in life* and *self-acceptance* (Ryff & Keyes, 1995; Ryff, 2013; Westerhof & Keyes, 2010). Keyes expanded the eudaimonic approach to include the domain of social well-being as he believes that functioning optimally in community is an important aspect of well-being. He found the following 5 facets: *social coherence, social acceptance, social actualization, social contribution* and *social integration* (Keyes, 1998; Lamers et al., 2011; Westerhof & Keyes, 2010).

Thus, results from various studies support the conclusion, that emotional, psychological and social well-being are considered to be related but still distinct domains of well-being (e.g. Westerhof & Keyes, 2010; Lamers et al., 2011; Joshanloo & Lamers, 2016; Joshanloo & Jovanović, 2017). Overall, it is not only important to define the concept of well-being per se; equally important is the question of the determinants that are associated with well-being. Petra Ziegler (2020) describes these determinants in detail, naming intrapsychic variables, such as personality and genetics as the most important influencing factors. Interestingly, external factors for example culture, income and gender have a low influence on well-being, according to Ziegler (2020). Also in the work of Lyubomirsky et al. (2005), the authors suggest that a wide variety of factors influence well-being, interchanging the terms between happiness and well-being.

These factors are then categorized into three main predictors: genetics (50% influence on happiness), intentional activity (40% influence on happiness), and circumstances (10% influence on happiness).

Overall, while many theories examine well-being and plenty is already known about it, there is not enough information to provide a comprehensive well-being framework

that spans the construct of well-being in its entirety (Linton et al., 2016; van de Weijer et al., 2021). However, currently it is unknown, to what extent these domains differ or overlap, which well-being facets are interconnected and which are the most central facets. Extracting this information can help to get a new perspective on well-being, it can help to filter out the most important domains and facets and this information can then be used for other areas such as the healthcare, in order to optimize interventions, for instance.

The construct of well-being has been studied with factor analytic methods (Joshani & Jovanović, 2017; van de Weijer et al., 2021). However, in factor analytic models and in most clinical psychology research, the predominant theory is the latent-variable theory, which assumes that there is a latent entity behind a psychological construct, e.g., a mental disorder, for which symptoms are the indicators and the symptoms are due to a latent cause (Herzberg & Wildfang, 2018).

The disadvantage of this factor analysis is that important information about the importance and effects of individual facets of well-being can be lost if they are not explicitly examined. Therefore, in order to understand a psychological construct better, one must also examine the role that each individual part play in the overall concept, which can be better represented in a psychometric network (Borsboom et al., 2021). Although well-being has been studied mainly with factor analyses, there is no universally complete concept of well-being that takes all facets into account (Linton et al., 2016; van de Weijer et al., 2021). A possible approach in understanding the architecture of well-being are psychometric network models, as conducted in this study. To introduce the reader to this method, the main advantages, key terms and components are explained below.

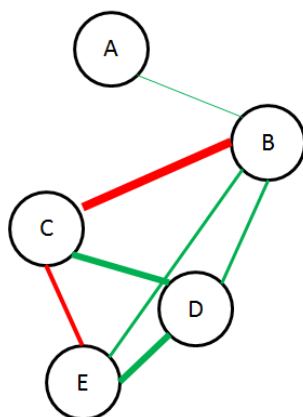
Psychometric Network Analysis in Well-being Research

Psychometric network models, are a relatively new approach, conceptualizes psychological concepts as emergent systems of interconnected variables that can be examined at the domain or item level (Blasco-Belled & Alsinet, 2022; Cramer et al., 2012). Psychological well-being is defined in the network model as a system in which the construct emerges from all interacting indicators (domains and facets/items). It is assumed that these indicators form the basis of the network structure and are not merely the cause or by-product of well-being, as is the case in factor models (van de Weijer et al., 2021). The network approach can then provide valuable insights to assess which of these indicators (domain and facets/items) are more relevant and important to well-being.

In particular, variables in network models are called *nodes*, and the connections between them, representing positive or negative correlations, are called *edges* (Constantini, 2014, Constantini et al., 2015; Epskamp et al., 2018). Notably, one of the most important advantages of the network approach is the concept of *centrality*, which can be used to show, which the most relevant components of a network are. *Centrality* indicates the importance of the role an item plays in the context of all other items in the whole network, which means items (or nodes) with high *strength centrality* indicate that these items have the most and the strongest associations with other items in the network and have a key role in the overall construct (Baindurashvili, 2021; van de Weijer et al., 2021). And lastly, *density* refers to the number of connections that all items have, the denser a network is, the more interconnected the items are. For example, a 5-node (circle A, B, C, D & E) and 7-edges (green and red lines that connect the nodes) network graph is shown in Figure 1.

Figure 1

A Self-elaborated Hypothetical Network with five Nodes (A, B, C, D, E) and seven Edges (connecting lines)



Note. Green edges represent a positive connection between nodes and red edges negative connection. Self-elaborated for explanatory purposes.

In this regard, the network approach assumes that when one symptom is activated, it can activate other symptoms and if strong enough, it can even activate an entire construct (Borsboom, 2017). Based on Figure 1, one could say that when node B is activated and is strong enough, it can activate all other nodes. An advantage of this approach is that by plotting item correlations on a graph, individual facets, domains or the entire construct can be better revealed and visualized (Blasco-Belled & Alsinet, 2022).

Furthermore, network research is a recent advance in several areas of psychology to describe psychological phenomena, however, the vast majority of network analyses are concerned with psychopathology or the relationship between well-being and mental disorders conducted in a clinical sample such as post-traumatic stress disorder (Fried et al., 2018), eating disorders (de Vos et al., 2021) or depression (van Borkulo et al., 2015). In a study on network structure of eating disorder patients, de Vos et al. (2021) found that psychological well-being was the most central domain of the mental health network, with emotional well-being and general psychopathology following. A network analysis study conducted by Govorova et al (2020), examined the relationships between and effects of school-related factors on various aspects of well-being, the findings showed that the node

with the strongest influences was self-efficacy. Students who had faith in their abilities, particularly in the face of challenging circumstances, and who believed that their lives have meaning and purpose were also generally happier (Govorova et al., 2020). A study conducted with Chinese population examined the network structure of adolescent well-being traits and found that cheerfulness, engagement, and optimism for the future are most central to well-being (Zeng et al., 2019). Blasco-Belles and Alsinet (2022) did a network analysis of Ryff's psychological well-being scale and found four domains with self-acceptance, life purpose, and environmental mastery clustered together and self-acceptance was revealed as the most central facet in the psychological well-being structure. Heshmati et al. (2020) assessed psychological well-being in early adulthood based on Seligman's PERMA model and found that positive relationships and positive emotions are most central to young adults' daily well-being.

Taken together, there are only few network studies that examine solely the construct of well-being. Thus, next to study the network of well-being it is also important to find out what are important factors that influence well-being, such as gender and income.

Differences of Well-being based on Gender

Gender differences in well-being have also been studied for some time. However, there are often inconsistent results, with some studies finding no significant difference in well-being, others showing significant differences and in some cases the results are also diverse within the gender groups (Batz & Tay, 2018). For instance, Stevenson and Wolfers (2009) found that men have higher levels of well-being, whereas other studies have shown that women have significantly higher levels of well-being (e.g. Fujita et al., 1991). In a meta-analysis, 46 empirical studies ($N = 11,772$) from 1980 to 2017 were analyzed to examine possible gender differences in life satisfaction among children and adolescents.

The results showed that life satisfaction remains the same across gender groups, but with a slight difference in favor of male participants (Chen et al., 2020). Furthermore, a different meta-analysis ($N = 1,001,802$) regarding gender differences in subjective well-being found no significant differences (Batz-Barbarich et al., 2018). Further, a study examining well-being in the Dutch population found no gender differences in social and psychological well-being. However, women scored better than men did in emotional well-being (Joshnloo & Lamers, 2016).

In summary, the studies come to different results about the influence of gender on well-being, so it is of interest to see what results and insights network analysis can contribute to this field of research.

Differences of Well-being based on Income

Several researchers have found it difficult to determine the relationship between income and well-being (Frey & Stutzer, 2002; Diener et al., 1999; Argyle, 1999). A study by Cummins et al. (2003) have concluded that, on average, income or the financial situation makes a positive but very small contribution to well-being. An important discovery is that money affects well-being when it is used to satisfy needs (Diener & Biswas-Diener, 2002). In general, associations between income and well-being (usually measured by life satisfaction) are stronger for individuals at lower economic levels (Biswas-Diener, 2008). Paid employment is critical to individuals' well-being because it provides them with direct access to resources and, for some, promotes satisfaction, meaning and purpose (Warr, 2003). Unemployment, and thus likely no or little income, has negative effects on well-being in both the short and long term (Sun et al., 2016).

However, there are no studies that examine the relationship between income and well-being using network analysis. Despite the recent growth of network models of well-being, this study can make a valuable contribution to ongoing studies as it does not address

psychopathology or examine the relationship between well-being and mental disorders in a clinical sample.

The Current Study

The aim of this study is to gain insight into the network structure of well-being in the Dutch general population. Moreover this study's goals are: finding the most impactful facets/items, showing how clearly delineated or interconnected different well-being facets from different domains are, how items correspond and cluster together, to learn how EWB, PSW and SWB relate to each other and what effects the variables gender and income have on the network structure of well-being.

The first research step is to explore the network structure of well-being in a sample of Dutch population using the Mental Health Continuum-Short Form (MHC-SF; Keyes, 2002) and to investigate the most central facets/items of well-being in the network. The second step is to examine gender differences in the network structure of well-being and to look for gender differences regarding the most essential facets of the three well-being domains. The final goal is to see if there are any significant differences regarding the most central facets of well-being based on income. In summary, the research questions (RQ) of this study are as follows:

RQ1.1: What is the network structure of well-being in the general Dutch population?

RQ1.2: What are the most central nodes of well-being domains in the network structure of the general Dutch population?

RQ2: Are there differences in the network structure and in the node strength centrality of the well-being domains based on gender?

RQ3: Are there differences in the network structure and in the node strength centrality of well-being based on low-, middle- and high income?

Methods

Participants and Procedures

This study used data from the LISS (Longitudinal Internet Study in the Social Science) panel of CentERdata, an internet panel for longitudinal studies in the social sciences administered by CentERdata in Tilburg, the Netherlands. The LISS panel represents 5,000 households randomly selected from municipal registers in the Netherlands. Household members were asked to complete online questionnaires each month. In one-third of the households, a CentERdata member was selected to complete a mental health module in December 2007, March 2008, June 2008 and September 2008. We used the data from December 2007 for this study ($N=1,662$, response rate = 69%). Of the 1,662 participants, 828 (49.8%) were men and 834 (50.2%) were women, aged 18 to 87 years (mean=47.61, $SD=17.74$). Among these, those aged 18 to 34 years accounted for 30.6%, those aged 35 to 54 years for 30.2%, and those aged 55 years and older for 39.2% of the participants. Regarding earning information, 244 participants have indicated that they have zero net income. The remaining 1,418 participants had a net income of at least 40€ and at most 165.216€/per month ($M=2014,62€$, $SD=7.687,23€$, $Median=1450€$). Among them are 10 outliers, 5 participants indicated that they have less than 100€ and the other 5 persons indicated that they have more than 88.000€ net income/per month (without these outliers the figures are as follows: $M=1576,27€$, $SD=903,21€$, $Median=1450€$).

Measures

To assess well-being the Mental Health Continuum-Short Form (MHC-SF; see the entire questionnaire in Appendix A) was used (Keyes, 2002). The MHC-SF assesses emotional, social and psychological well-being (see Table 1 for all facets/items) during the previous month with 14 items on a 6-point Likert scale (1=*never*, 2=*once or twice a month*, 3=*about once a week*, 4=*two or three times a week*, 5=*almost every day*, 6=*every day*). The

items were translated into Dutch and backwards into English to ensure comparability (Lamers et al., 2011). Emotional well-being domain (EWB) consists three facets/items, psychological well-being (PWB) consists six facets/items and the social well-being domain (SWB) consists five facets/items. The Cronbach's alpha reliability estimates of the MHC-SF were .83 for emotional well-being, for social well-being .74 and .83 for psychological well-being (see Table 1 for further detail).

Table 1

<i>14 Items of the Mental Health Continuum- Short Form (MHC-SF)</i>		
<i>Domain (facet/Item)</i>	<i>In the past month, how often did you feel...</i>	<i>Cronbach's α</i>
<i>N</i>	1662	
<i>Emotional well-being (EWB)</i>		
		.83
Happiness (HAP)	...happy?	
Interest (INT)	...interested in life?	
Life satisfaction (LFS)	...satisfied?	
<i>Social well-being (SWB)</i>		
		0.74
Social contribution (SCN)	...that you had something important to contribute to society?	
Social integration (SIN)	...that you belonged to a community (like a social group, your neighborhood)?	
Social actualization (SAC)	...that our society is becoming a better place for people?	
Social acceptance (SCC)	...that people are basically good?	
Social coherence (SCO)	..that the way our society works makes sense to you?	
<i>Psychological well-being (PWB)</i>		
		0.83
Self-acceptance (SEA)	...that you liked most parts of your personality?	
Mastery (MAS)	...good at managing the responsibilities of your daily life?	
Positive relations (PRL)	...that you had warm and trusting relationships with others?	
Personal growth (PGO)	...that you have experiences that challenge you to grow and become a better person?	
Autonomy (AUT)	...confident to think or express your own ideas and opinions?	
Purpose in life (PUL)	...that your life has a sense of direction or meaning to it?	

In the study of the variable income, we followed the suggestion of Cummins (2000), which states that in the analysis of the financial situation for well-being, income within society should be divided into three categories: high-, middle- and low-income. The Deutsche Institut für Wirtschaftsforschung (German Institute for Economic Research) also distinguishes three categories of income classes and puts them into perspective using the median disposable income. Thus, those who earn 150% or more of the median income are considered wealthy. The middle class is defined as those earning between 70% and 150% of the median income, and the low-income group includes persons earning less than 70% of the median income (Goebel et al., 2019). The Dutch net median income in 2007 was 24.800€ according to Statistics Netherlands (<https://www.cbs.nl/en-gb>), from which we derived a low net income group from 1€ to 1.446€/per month, a middle income group from 1.447€ to 3.099€/per month and a high income group above 3.099€/per month.

Data Analyses

For the statistical analysis, the R and RStudio Team software was used (see Appendix B for the R code). The data set included 1,662 participants without missing data. First, all variables in the data set that were not the subjects of this work were removed. To check item redundancy, we used the goldbricker function available in the networktools r package (Jones, 2018). Using this function, one is able to identify items that are insignificant to the network because they are too highly correlated with other items ($r \geq .7$). We then extracted subsamples for gender (female, male) and income (low-, middle-, and high-income). It was found that the sample of the high-income group is $n=75$. Therefore, we followed the recommendations of Epskamp et al. (2018), stating that for a reliable network analysis, the sample size should be at least 250 to 500. Consequently, we excluded the high-income group.

In the next step, networks for the entire sample, female group, male group, low-income group and middle-income group were estimated and visualized with the R package `qgraph` (Epskamp et al., 2012). To estimate the partial correlation, a Gaussian Graphical Model (GGM) was chosen as the best estimation method for our data. The Least Absolute Shrinkage and Selection Operator (LASSO) with Extended Bayesian Information Criterion (EBIC) model selection was applied to limit the number of spurious edges and therefore, leading to a sparse network that describes data parsimoniously (Haselbeck & Waldorp, 2015; Epskamp & Fried, 2018; Zeng et al., 2019). The LASSO is a regularization technique that shrinks all connections and sets small coefficients to zero to get a sparse network with few edges to illustrate associations (Blasco-Belled & Alsinet, 2022). To identify the central elements of well-being, we estimated the node strength centrality of the well-being network. Although centrality can also be calculated using closeness (sum of the shortest paths from the node of interest to all other nodes in the network) or betweenness (the relative frequency of a node of interest in the shortest path between other node pairs) (Zeng et al., 2019). Node strength centrality (S) indicates how strongly a node or item is directly connected to other nodes, based on the absolute sum of edge weights connected to a node (Epskamp et al., 2012). To interpret the relevance of a node, researchers suggested relying on node strength rather than closeness or betweenness measures, as these cannot be considered valid and meaningful for centrality in psychometric networks (Isvoranu & Epskamp, 2021; Zeng et al., 2019; de Vos et al., 2021). To identify the most central items the `centralPlot` function of the `qgraph` was used (Epskamp et al., 2012). After network estimation, the stability and accuracy of all networks were tested. Therefore the R package `bootnet` was used to show accurate results (Epskamp & Fried, 2018). Following suggestions of previous study from Epskamp et al. (2018) 1000 bootstraps were used. The accuracy of the edge-weights was estimated by calculating nonparametric bootstrapped

95% confidence intervals (*CI*s). Then, the stability of the strength centrality was indexed by the correlation-stability coefficient (*CS*) with 1000 bootstraps. The correlation-stability coefficient tests the maximum proportion of cases that can be dropped from the dataset such that with 95% probability the correlation (*cor*) between original centrality indices and centrality indices based on the subsets remains above (by default) 0.7. In simplified terms, it shows how much of the original sample can be excluded without affecting the correlations between the original sample and the subsets. Thus, Correlation-stability coefficients are recommended to not be below 0.25 and preferably be above 0.5 to be considered stable (Epskamp & Fried, 2018).

Differences in networks and network structures as well as centrality indices were tested lastly using the R package Network Comparison Test (NCT) (van Borkulo, 2016). The NCT compares two networks using a variety of invariance measures, including edge invariance, global strength invariance, and network structure invariance (van Borkulo, 2018). With the NCT method, moreover, the structure of the network can be examined, differences in the strength of edges and the node strength centrality can be determined and whether the overall level of connectivity between groups is equal or significantly unequal (van Borkulo, 2018; Baidurashvili, 2021). With this test the female and male networks and both income networks are examined on overall network structure and centrality. Overall, a p-value of $\leq .05$ indicates a significant difference for all analyses in this study.

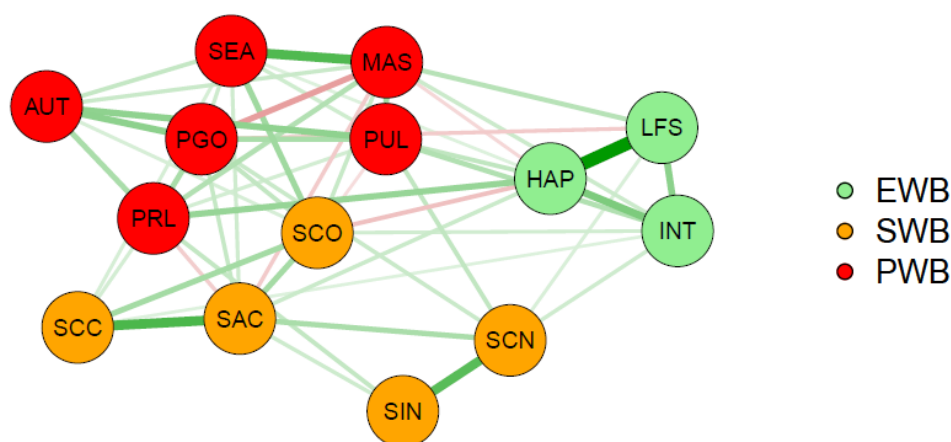
Results

Network Structure in the General Dutch Population

The goldbricker function suggested no reductions for the 14 items of the Mental Health Continuum-Short Form. The visualization of the network of the whole sample ($N=1,662$) is presented in Figure 2. The network has 51 weighted edges, of which 37 edges are positive correlations and 14 edges are negative correlations.

Figure 2

Network of the 14 MHC-SF Items for Entire Sample



Note. Items belonging to the same domain appear in the same color. Green edges represent positive regularized partial correlations between nodes, while red edges represent negative regularized partial correlations. The thickness of the edge represents the strength of the correlation. EWB=emotional well-being, PWB=psychological well-being, SWB=social well-being. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

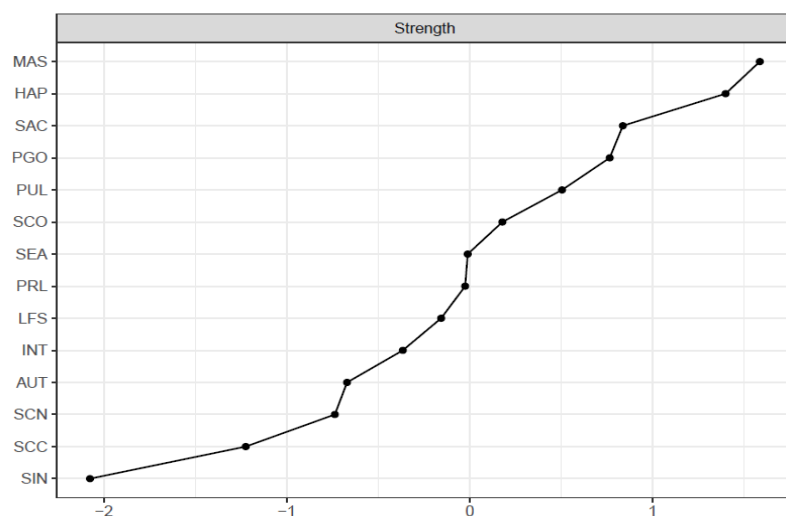
In Figure 3 the node strength centrality (S), which indicates how strong and intensive the connection of a node is to other nodes in the network, based on the nodes weight, is visualized. Nodes/items with high strength centrality have a higher ability to distribute and control information in the network (Epskamp et al., 2012). Lower, negative Z-scores indicate nodes with lower strength, while higher, positive Z-scores indicate nodes with high centrality. The nodes with the highest node strength centrality, were *mastery* ($S= 1.59$) and *happiness* ($S= 1.4$). The nodes with the lowest node strength centrality were *social integration* ($S= -2.08$) and *social acceptance* ($S= -1.22$).

The strongest edges (r = correlations) were found between the facets *happiness* and *life satisfaction* ($r=.49$), *social actualization* and *social acceptance* ($r=.35$), *self-acceptance* and *mastery* ($r=.34$) and between *social contribution* and *social integration* ($r=.32$), which

means that these pairs have the highest correlation to each other and therefore influence each other the most (see Appendix A Table A1 to find all correlations).

Figure 3

Standardized Node Strength Centrality Estimates of the 14 MHC-SF Items for Entire Sample



Note. There are z-scores instead of raw centrality indices. The higher the z-score is the higher the centrality coefficient is for each item. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Network Stability Estimation

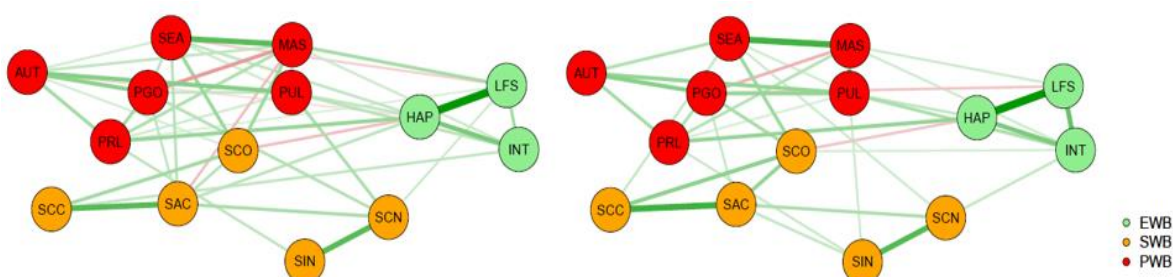
We evaluated the stability of the estimated network and the accuracy of centrality measures (results are presented in Figure A1 and Figure A2 in Appendix A). The edge weight bootstrap revealed that the network is accurately estimated: there is overlap among the 95% bootstrapped confidence intervals (CIs) of edge weights and the correlation-stability coefficient (CS- coefficient) indicating that the strength centrality ($CS (cor=.7) = .60$) is stable under different subsamples.

Differences in Network Structure based on Gender

The networks for females ($n=834$) and males ($n=828$) were estimated and are presented in Figure 4. The female network has 37 weighted edges from which 6 are negative correlations. The male network is more interconnected with 10 negative and 33 positive weighted edges/correlations.

Figure 4

Network of the 14 MHC-SF Items for Male (left Graph) and Female (right Graph)



Note. Items belonging to the same domain appear in the same color. Green edges represent positive regularized partial correlations between nodes, while red edges represent negative regularized partial correlations. The thickness of the edge represents the strength of the correlation. EWB=emotional well-being, PWB=psychological well-being, SWB=social well-being. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Female Network

In Figure 5 the node strength centrality (S) for the female and male network is visualized. The nodes with the highest node strength centrality for the female network were *happiness* ($S=1.36$) and *purpose in life* ($S=1.33$). The nodes with the lowest node strength centrality for the female network were *social integration* ($S=-1.61$), *social contribution* ($S=-1.33$), *social acceptance* ($S=-1.32$) and *autonomy* ($S=-1.05$).

The strongest edges/correlations in the female network were found between the facets *happiness* and *life satisfaction* ($r=.47$), *social actualization* and *social acceptance* ($r=.35$) and between *social contribution* and *social integration* ($r=.31$), which means that changes in one facet will most likely lead to a change in the other facet (see Appendix A Table A2 to find all correlations).

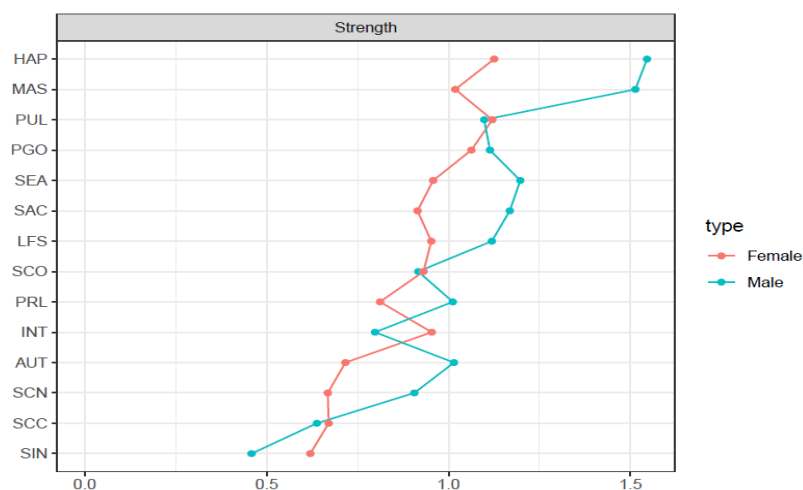
Male Network

For the male network the nodes with the highest node strength centrality (S) were *happiness* ($S=1.73$) and *mastery* ($S=1.62$) and the nodes with the lowest node strength centrality were *social integration* ($S=-1.96$) and *social acceptance* ($S=-1.35$).

The strongest edges in the male network were found between the facets *happiness* and *life satisfaction* ($r=.50$), *social contribution* and *social integration* ($r=.33$), *social actualization* and *social acceptance* ($r=.33$) and between *self-acceptance* and *mastery* ($r=.32$) (see Appendix A Table A3 to find all correlations).

Figure 5

Standardized Node Strength Centrality Estimates of the 14 MHC-SF Items for Gender



Note. There are z-scores instead of raw centrality indices. The higher the z-score is the higher the centrality coefficient is for each item. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Network Stability Estimation

For both networks, we also evaluated the stability of the estimated networks and the accuracy of their centrality measures (results are presented in Figure A3 to Figure A6 in Appendix A). The edge weight bootstrap revealed that the male and female networks are accurately estimated: there is overlap among the 95% CIs (confidence intervals) of edge weights and the CS-coefficient (correlation-stability coefficient) indicates that the strength centrality ($CS (cor=.7) = .46$) for male group and ($CS (cor=.7) = .33$) for female group is stable under different subsamples. In simplified terms, the correlation-stability coefficient shows how much of the original sample can be excluded without affecting the correlations between the original sample and the subsets.

Network Comparison Test

The network comparison test revealed that the mean difference ($Mdiff$) of the overall network structure of male and female networks is statistically not significant ($Mdiff = .19, p = .055$), so the female and male well-being overall networks can be considered relatively equal. Single significantly different edges (see Table A6 in Appendix A) in the female and male networks were not further investigated, because no overall differences were found. These different edges are correlations between two items that are significantly different in the male-female networks. The global network strength test revealed significant differences ($Sdiff = .99, p < .01$) between the strength centrality indices of the female network ($S = 6.26$) and the male network ($S = 7.25$). To be more specific, the strength centrality of the male network is higher (i.e. more stronger connections within the network) than the female network (see Figure 5 above).

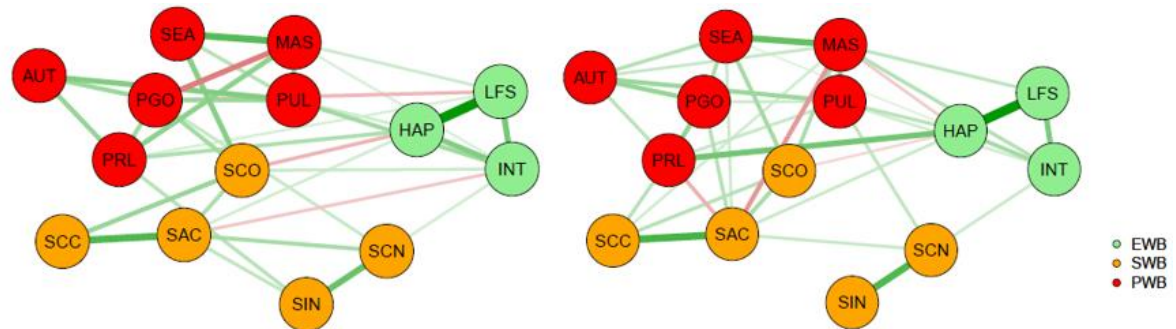
Differences in Network Structure based on Income

The networks for low-income ($n = 699$) and middle-income ($n = 640$) were estimated and are presented in Figure 6. The low-income network has 37 weighted edges from which

8 are negative correlations. The middle-income also has 37 weighted edges (4 negative edge nodes).

Figure 6

Network of the 14 MHC-SF Items for Low-Income (left) and Middle-Income (right Graph)



Note. Items belonging to the same domain appear in the same color. Green edges represent positive regularized partial correlations between nodes, while red edges represent negative regularized partial correlations. The thickness of the edge represents the strength of the correlation. EWB=emotional well-being, PWB=psychological well-being, SWB=social well-being. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Low-income group

In Figure 7 the node strength centrality for the two different income networks is visualized. The nodes with the highest node strength centrality (S) for the low-income network were *personal growth* ($S=1.28$) and *happiness* ($S=1.2$). The nodes with the lowest node strength centrality for the low-income network were *social acceptance* ($S=-1.53$) and *social integration* ($S=-1.47$). Strength centrality (S) indicates how strong and intensive the connection of a node is to other nodes in the network, based on the nodes weight. Nodes with high strength centrality have a higher ability to distribute and control information in the network (Epskamp et al., 2012).

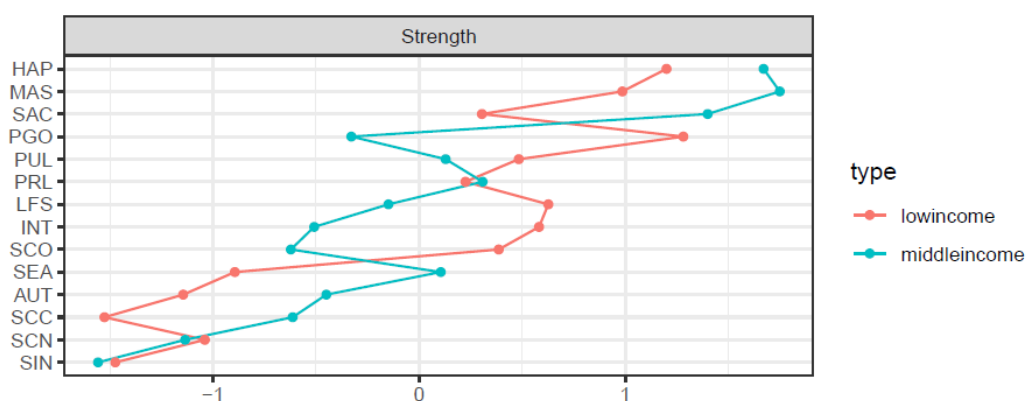
The strongest edges (r = correlation) in the low-income network were found between the facets *happiness* and *life satisfaction* ($r=.49$), *social actualization* and *social acceptance* ($r=.34$) and between *self-acceptance* and *mastery* ($r=.32$), which means that changes in one facet will most likely lead to a change in the other facet (see Appendix A Table A4 to find all correlations).

Middle-income group

For the middle-income network the nodes/items with the highest node strength centrality were *mastery* ($S=1.75$), *happiness* ($S=1.67$) and *social actualization* ($S=1.4$) and the nodes with the lowest node strength centrality were *social integration* ($S=-1.56$) and *social contribution* ($S=-1.13$). The strongest edges (r = correlation) in the middle-income network were found between the facets *happiness* and *life satisfaction* ($r=.51$), *social actualization* and *social acceptance* ($r=.37$) and between *social contribution* and *social integration* ($r=.35$) (see Appendix A Table A5 to find all correlations).

Figure 7

Standardized Node Strength Centrality Estimates of the 14 MHC-SF Items for Income



Note. There are z-scores instead of raw centrality indices. The higher the z-score is the higher the centrality coefficient is for each item. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Network Stability Estimation

For both networks we also evaluated the stability of the estimated networks and the accuracy of their centrality measures (results are presented in Figure A7 to Figure A10 in Appendix). The edge weight bootstrap revealed that the low-income network and the middle-income network are accurately estimated: there is overlap among the 95% CIs (confidence interval) of edge weights and the CS- coefficient (correlation-stability coefficient) indicates that the strength centrality for low-income group ($CS (cor=.7) = .29$) and for middle-income group ($CS (cor=.7) = .34$) are stable under different subsamples.

Network Comparison Test

The network comparison test revealed that the mean difference ($Mdiff$) of the overall network structure of both networks are statistically not significant ($Mdiff = .25, p = .15$), so the low-income and middle-income overall networks can be considered relatively equal. The global network strength test also revealed no significant differences between the strength centrality indices in the networks. Single significantly different edges (see Table A7 in Appendix A) in the low-income and middle-income networks were not further investigated, because no overall differences were found.

Discussion

The present study investigated the network structure of well-being in a Dutch sample using Keyes's (2008) concept of well-being. For this purpose a network analysis was conducted. To the best of the author's knowledge, this is the first study to investigate the well-being structure in the general Dutch population with a network approach. The most important facets of the domains emotional, psychological and social well-being were examined. It was found that *happiness* and *mastery* are the strongest and most influential facets in the construct, showing mostly positive associations with all other facets and therefore have a key role in the well-being network. Activating or decreasing these facets may result in activating or decreasing more facets that are connected too as well.

In contrast, *social integration* (in all networks examined) and *social acceptance* (in all networks examined except the middle-income group) were found to be the well-being facets with the lowest effect in the networks.

In addition, we investigated whether gender and income have an influence on the structure of well-being. When comparing the network structure of well-being of women and men and of low-income and middle-income, no significant differences were found for the overall networks. By inspecting the 14 items of the Mental Health Continuum-Short Form for redundancy, it was confirmed that the MHC-SF is a reliable questionnaire. All items were connected to at least 3 other items, indicating that all items are significant for the network, as also demonstrated in previous studies. Furthermore, as in other studies (e.g. Keyes et al., 2008; Lamers et al., 2011; Joshanloo & Jovanović, 2017), the 3 domains of well-being were also found here and again these are shown to be three related but distinctive domains. Moreover, it is consistent with other studies showing that emotional well-being, social well-being and psychological well-being are strongly correlated (Keyes et al., 2008; Lamers et al., 2011; Joshanloo & Jovanović, 2017).

Previous well-being research, mainly using factor analytic methods, has examined differences in the construct well-being in different cultures, but mostly at the domain level and not at the item/facet level (e.g. Joshanloo & Jovanović, 2016). Furthermore, well-being research is predominantly focused on factors that influence the level of well-being (e.g. Diener et al., 2018).

Meaning of Happiness for Well-being

The high correlation between happiness and well-being is evident, as the two terms are used interchangeably (e.g. Lyubomirsky et al., 2005; Zanon et al., 2022; Xiao et al., 2016). Similarly, to the results of this study, there is evidence of a strong correlation between happiness and well-being and that happiness is considered an essential key factor of psychological well-being and has a strong relationship with several dimensions of well-being (Diener et al., 2002; Seligman & Csikszentmihalyi, 2000). For example, those who can maintain a positive attitude and higher levels of happiness are more able to cope with stressors, have higher self-esteem, are psychologically healthier, are often more successful at work, and have better social relationships. (Lyubomirsky et al., 2005; Diener et al., 2018; Sheldon & Lyubomirsky, 2006; Diener, 2000). Thus, cross-cultural happiness research has found that collectivist cultures generally value social membership, social cohesion, and positive personal experiences in the social context more when assessing their happiness, whereas individualist cultures -such as the Netherlands- primarily consider personal experiences when assessing their overall life satisfaction (Wasil et al., 2021). However, the vast majority of these studies examine which influencing factors increase the level of happiness. But the fact that happiness was found to be the most highly related item in all the networks examined in this study, even though it did not have the most correlations, but had the strongest correlations, confirms once again the importance of this facet for the construct of well-being.

To sum up, reviewing the findings, we can assume that happiness is a key factor of well-being that creates a kind of "virtuous circle" in which positive emotions and an optimistic outlook on life contributes to a fulfilling and satisfied life, which in turn result in a state of improved well-being.

Meaning of Mastery for Wellbeing

This study found mastery to be one of the most strongly associated facet in the network. In all 5 networks examined, mastery is one of the most important facets and has some of the highest number of correlations. Similarly, de Vos and colleagues (2021), in a study of the relation between eating disorders and well-being, identified environmental mastery as one of the bridge symptoms and therefore an important facet. Furthermore, in another study, Burns et al. (2011) demonstrated that mastery was positively correlated with subjective well-being. However, environmental mastery refers to the sense that a person can master owns environment and cope with life's demands and challenges.

Hence, Deci and Ryan's (2012) self-determination theory could offer an explanation for the importance of mastery for well-being network. According to this theory, individuals have an innate motivational tendency to experience themselves as effective, functioning, and competent. Thus, when persons experience environmental mastery, a basic need is satisfied, which then in turn leads to increased well-being. In fact, also in Grawe's concept of four basic psychological needs, in which the need for orientation and control is most similar to the concept of environmental mastery, it is assumed that these needs are present in all humans and that their violation or persistent nonfulfillment leads to impairments in mental health and well-being (Ghadiri et al., 2012).

Meaning of Social Integration and Social Acceptance for Well-being

The present study finds that social integration and social acceptance are not only most weakly associated with other facets of well-being, but also have the fewest

connections to other facets, which suggests that these facets play a minor role in experiencing well-being in the Dutch population. In a study by Joshanloo (2016) with participants from New Zealand and USA, he also found relatively weak loadings for social integration. There are several factors that could explain these results. First, social and cultural factors may also have an impact on subjectively perceived well-being, because depending on the country and culture, the strength of a person's integration into a community may be higher or lower, and this may affect well-being differently (Diener & Suh, 2003). For example, a person's social integration plays a rather minor role in Western industrialized countries compared to many Asian countries, where the focus is on the community rather than the individual (Nisbett, 2019). This might explain why social integration and social acceptance play a less important role in our study of well-being in the Dutch population. Therefore, future research is needed to investigate these cultural differences.

Additionally, further reasons why the influence of these two facets on well-being is low, may be that individual factors such as self-acceptance and self-esteem play a more important role. Even if a person is socially accepted and integrated, their subjective well-being may be impaired if they reject themselves or have low self-esteem (Orth & Robins, 2014). Further, a network analysis of the Ryff psychological well-being scale, conducted by Blasco-Belled & Alsinet (2022), has indicated that self-acceptance is the most central facet. Furthermore, in that study it was also demonstrated that self-acceptance, life purpose, and environmental mastery are highly interconnected, which is comparable to the results of this study (purpose in life was found to be the second strongest facet in the female network in our study).

Therefore, external social aspects are probably less important for well-being than internal processes, this might also be the reason why the domain social well-being (3,3) has

the lowest mean compared to emotional- (4,7) and psychological well-being (4,2) in this study.

Meaning of Gender for Well-being

In this study, it was found that the overall network structure of well-being of female and male in the Dutch population does not differ significantly. In other words, the psychometric properties of well-being of both genders are more similar than they are different. This is consistent with previous scientific work. In a Serbian sample in which the factor structure of the MHC-SF was examined, the authors found no significant gender differences (Joshanloo & Jovanovic, 2016). Moreover, Joshanloo reports that he did not detect significant overall differences with samples from New Zealand and the United States (Joshanloo & Jovanovic, 2016). Furthermore, in a Vietnamese sample, no gender differences could be found (Rogoza et al., 2018). However, in a study with Iranian participants, men were discovered to score higher on social well-being than women and in a study with Dutch participants, males were found to score significantly lower on emotional well-being than women (Joshanloo, 2016; Joshanloo & Lamers, 2016).

Hence, also in the present study there are specific individual differences in the two networks. Thus, the male network (43 correlations among the facets) was found to be more inter-correlated than the female network (37 correlations). Furthermore, the most central facets differ between the genders, for females, these are *happiness* and *purpose in life*, and for males, they are *happiness* and *mastery*. In addition, men show a significant higher overall strength of the network, by considering the weights of all correlations, which indicates that the connections within the male network are overall stronger. Moreover, the correlations between individual facets (7 correlations in total) are significantly different between the genders. The results of the present study, as well as previous findings, suggest

that the structure of the construct well-being is inherently consistent and that gender is more likely to influence levels of well-being.

Thus, Hyde (2007) concluded that it is important to explain why gender differences in subjective well-being may not be expected by referring to her gender similarity hypothesis (Hyde, 2005), which suggests that gender differences are often small or non-existent.

Meaning of Income for Well-being

In this study, it was found that there is no overall significant differences between the network structure of low- and middle-income groups in the Dutch population. However, there are specific individual differences when comparing the two networks in the present study. Although both networks have the same number of correlations (37) between the facets, the low-income group has twice as many negative correlations (8) as in the middle-income group (4). The correlations between the facets (7 correlations in total) also differ significantly between the income groups. The results of the present study suggest that the structure of the construct well-being is consistent in itself.

Thus, many studies focus on the influence of income on the level of well-being, and there are several theories that identify factors behind income as indicators for well-being (Diener & Biswas-Diener, 2002; Kahneman & Deaton, 2010; Easterlin 2001; Stangl, 2023; Clark et al., 2008). Stangel (2023) reports that three quarters of the relationship between income and well-being could be explained by the factor *control over one's life*, rather than money or wealth, which again supports the finding of this study, namely that the facet mastery, which is related to control over one's life, is more important for the network structure of well-being.

Theoretical Contributions and Implications

As described in the introduction, there is no consensus on the measurement of well-being, despite extensive scientific work (Linton et al., 2016). However, this empirical work targets a better understanding of the complexity of well-being. Furthermore, this network analysis provides a more nuanced understanding of the complexity of well-being by examining its most important facets (happiness, mastery, purpose in life and personal growth) and the interrelationships between the different facets. In addition, the network structures of well-being were examined based on the variables gender and income. By mapping the network of well-being, this study can provide insight into the underlying mechanisms of well-being, we know the correlations of each facet, their importance to the overall network, and thereby know which facets make up a cluster. As already described in the previous sections this study is also a validation of existing studies (e.g. Westerhof & Keyes, 2010; Lamers et al., 2011; Joshanloo & Jovanović, 2017; Joshanloo & Lamers, 2016).

The findings of the network analysis approach could be used to improve existing well-being questionnaires, by better filtering out items that play a minor role such as social integration and social acceptance and better highlighting those items that have a high effect on the network like happiness and mastery. Similar to the broaden-and-build theory (Fredrickson, 2013) which posits that positive emotions such as happiness expand an individual's consciousness and promote new, exploratory thoughts and actions, intentionally promoting key facets (happiness and mastery) could further build skills and psychological resources. The improvement of an aspect which is most strongly associated may largely influence the overall well-being network and facilitate the well-being intervention gains (Zeng et al., 2019). When developing prevention and intervention programs, the results of this study, especially the findings of happiness and mastery as the

most central nodes, should be used to decide which components to focus on, since network research indicates that changes in central symptoms can lead to improvements in the entire mental health network (de Vos et al., 2021; Borsboom, 2017).

However, it is recommended to focus on well-being at the beginning of medical and psychological treatment and to include it in the treatment, because many studies have found that well-being is associated with benefits in health for example longevity, more effective immune system, decreased risk of illness, injury, and disease (Joshani & Jovanović, 2017; Frederickson & Levenson, 1998).

Longitudinal studies with multiple measurements can provide more detailed insights into associations between variables and potential causal determinants (de Vos et al., 2021). In addition, experience sampling studies can provide evidence about how networks evolve over time and whether changes in one node predict changes in another node. Currently, there are few network analyses that use experience sampling as a data collection method. For instance, Heshmati and colleagues (2020) developed a daily well-being assessment based on the PERMA model and found that having positive relationships and positive emotion were most central to early adults' daily well-being and that positive relationships are rather more important to well-being than just belonging to a community (Heshmati et al., 2020).

Strengths and Limitations

As in any scientific work, there are weaknesses and strengths in the present study. Since the present work is a cross-sectional study, this means that no causal conclusions can be drawn, but they can point to potential causal relationships as exploratory hypothesis-generating constructs (van de Weijer et al., 2021). Further, the most central nodes were considered to be those with a $S_{SD} \geq 1$, which is arbitrary, currently there is no rule for how many nodes should be considered central (de Vos et al., 2021).

Another important limitation is that differences between men and women were considered, especially in the present time when LGBT community is demanding their rights more strongly, another gender option should be considered, e.g., diverse to avoid discrimination. Another limitation is, that in comparison to national statistics, elderly, single, never married, widowers and immigrants are all underrepresented in the dataset (Lamers et al., 2011). A further limitation is that the sample is from 2007, today almost 16 years later and with the current economic and political developments in Europe (Covid pandemic and war in Ukraine and its consequences) many things have changed.

Another limitation is that there are many more participants in the low- ($n=699$) and middle income ($n=640$) group than in the high income group ($n=75$), as a result, no comparisons could be made to the high-income group. This would have been a particularly interesting comparison, as the difference in income between the low-income group and the high-income group is significantly greater than between the low- and middle-income groups. Moreover, the composition of the low-income group is not sufficiently accurate, this is because there are many participants who reported a monthly income of significantly less than 1000 euros. It is doubtful whether net income alone is sufficient to indicate well-being, since net income does not necessarily indicate a person's wealth. Moreover, as described above, income is unlikely to have a direct impact on the structure of well-being; rather, it is what the money is spent on that directly affects well-being. The sample also did not take into account the involvement of young people in education with little or no income and pensioners who no longer have an income from work. For these two groups, it is questionable to what extent their income correlates with well-being.

Regarding the nationality of the participants, it must be reminded that only persons living in the Netherlands and those understanding Dutch responded the questionnaire, leaving aside individuals that live in the Netherlands and do not speak Dutch. Furthermore,

the data was obtained only in the Netherlands, therefore, the results cannot be generalized to other populations or other cultures. It is important to conduct similar studies and to compare the results between countries or cultures.

The accuracy and reliability of the self-reported data may be limited due to social desirability, which can affect the validity of the network structure and reduce the data quality (Caputo, 2017). Another limitation of this study is that the complexity of well-being cannot be fully reflected even with a network analysis, there are simply too many factors that influence well-being and it is not possible to include every one of these factors in the analysis, therefore the results cannot be generalized to the entire well-being construct.

A strength of this study is, that psychometric network analysis provides a detailed analysis of the interrelationships between different facets and domains of well-being. All items were examined and correlated with each other. The benefit of this is that it allows revealing important structures in the data that would otherwise be challenging to uncover and there is less chance of overlooking crucial elements (Heshmati et al., 2020). Thus, when the main facets of the well-being network are discovered, it gains complexity and provides a more sophisticated insight. One advantage of this study is that it was a large sample ($n = 1662$) and the size is well suited for a network analysis (Epskamp & Fried, 2018). Additionally, a strength is that the accuracy of estimated network connections and the stability of the strength-centrality indices were assessed by using the bootstrapped difference test with 1000 subsamples and the correlation stability coefficient to increase confidence in the replicability of the estimated network structure and to show that the results were robust.

Future Research

Several areas of future research can be explored regarding network analysis of well-being. Future research could employ longitudinal designs to investigate how network structure changes over time and how this relates to changes in well-being. Longitudinal studies could also help to identify potential causal relationships between different symptoms or domains of well-being. New research could use multilevel analyses to examine how network structure varies across different levels of analysis, such as individual, group, and community levels. This approach could help identify how social and environmental factors impact network structure and well-being. Future research could investigate the effectiveness of interventions designed to modify network structure to improve well-being. For example, interventions targeting specific network nodes, for instance the facets happiness, mastery, purpose in life and personal growth could be evaluated to determine their impact on overall network structure and well-being.

Additionally should be observed how cultural and contextual factors may impact well-being. Future studies should examine other parameters in addition to the variables of gender and income. For example, it may be important whether the person is married, has children, is a housewife or househusband, or depends on the partner's income. It should also be investigated whether age plays an important role in the topic of well-being in order to develop intervention concepts specifically for the age groups.

The current study used only one measurement instrument, the Mental Health Continuum-Short Form, to assess psychological well-being. Although MHC-SF is a well-established survey (Lamers et al., 2011) and its psychometric properties have been tested, there are other well-established measurement instruments of well-being. Therefore, future studies should use other measurement tools to conduct a network analysis and see if the results are consistent.

Conclusion

Previous well-being research has mainly focused on the relationship between well-being and psychopathology. Psychometric network analysis has also predominantly taken this approach (e.g. Fried et al., 2018; de Vos et al., 2021; van Borkulo et al., 2015). A unique characteristic of this study is, that it is the first to exclusively investigate well-being and the influencing factors gender and income in the Dutch population with the psychometric network approach. New insights into well-being structure in the Dutch population were obtained through this study. One of the significant insights was to find happiness and mastery to be the most strongly correlated facets of well-being in the networks. The weakest and least correlated facets of well-being were found to be social integration and social acceptance. Overall, however, no significant difference was found between the gender networks and between the income networks, which suggests that the structure of the construct well-being is inherently consistent and these variables influence the level of well-being but not its psychometric structure.

However, these results of this explorative study can be used as a basis for further research of well-being in the Dutch population, and can be extended to other cultures to obtain an overall concept of well-being. The results can also be used for public mental health services, governments and primary care to design more effective interventions based on the results of this study to promote mental health. The findings of the present study contribute to the current debates among well-being research, as its findings broaden the understanding of well-being structure.

References

- Andrews, F. M., & Withey, S. B. (2012). *Social indicators of well-being: Americans' perceptions of life quality*. Springer Science & Business Media.
<https://doi.org/10.1007/978-1-4684-2253-5>
- Argyle, M. (1999). Causes and correlates of happiness. In: D Kahneman, E Diener, N Schwarz (Eds.) *Well-being: the foundations of hedonic psychology*. New York: Russell Sage Foundation, 307–322:353–373.
- Baindurashvili, G. (2021). *The psychometric network structure of maladaptive personality trait facets in eating disorder patients* (Master's thesis, University of Twente).
<https://purl.utwente.nl/essays/89083>
- Batz, C., & Tay, L. (2018). Gender differences in subjective well-being. In E. Diener, S. Oishi, & L. Tay (Eds.), *Handbook of well-being*. Salt Lake City, UT: DEF Publishers. <https://nobascholar.com>
- Batz-Barbarich, C., Tay, L., Kuykendall, L., & Cheung, H. K. (2018). A meta-analysis of gender differences in subjective well-being: Estimating effect sizes and associations with gender inequality. *Psychological science*, 29(9), 1491-1503.
<https://doi.org/10.1177/0956797618774796>
- Biswas-Diener, R. (2008). Material wealth and subjective well-being. *The science of subjective well-being*, 307-322. <https://hdl.handle.net/10037/2332>
- Blasco-Belled, A., & Alsinet, C. (2022). The architecture of psychological well-being: A network analysis study of the Ryff Psychological Well-Being Scale. *Scandinavian Journal of Psychology*, 63(3), 199-207. <https://doi.org/10.1111/sjop.12795>

- Borsboom, D., Cramer, A. O., Schmittmann, V. D., Epskamp, S., & Waldorp, L. J. (2011). The small world of psychopathology. *PloS one*, *6*(11), e27407.
<https://doi.org/10.1371/journal.pone.0027407>
- Borsboom, D., & Cramer, A. O. (2013). Network analysis: an integrative approach to the structure of psychopathology. *Annual review of clinical psychology*, *9*, 91-121.
<https://doi.org/10.1146/annurev-clinpsy-050212-185608>
- Borsboom, D. (2017). A network theory of mental disorders. *World psychiatry*, *16*(1), 5-13. <https://doi.org/10.1002/wps.20375>
- Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., ... & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*(1), 58.
<https://doi.org/10.1038/s43586-021-00055-w>
- Burns, R. A., Anstey, K. J., & Windsor, T. D. (2011). Subjective well-being mediates the effects of resilience and mastery on depression and anxiety in a large community sample of young and middle-aged adults. *Australian & New Zealand Journal of Psychiatry*, *45*(3), 240-248. <https://doi.org/10.3109/00048674.2010.529604>
- Caputo, A. (2017). Social desirability bias in self-reported well-being measures: Evidence from an online survey. *Universitas Psychologica*, *16*(2), 245-255.
<https://doi.org/10.11144/javeriana.upsy16-2.sds>
- Chen, X., Cai, Z., He, J., & Fan, X. (2020). Gender differences in life satisfaction among children and adolescents: A meta-analysis. *Journal of Happiness Studies*, *21*, 2279-2307. <https://doi.org/10.1007/s10902-019-00169-9>

- Clark, A. E., Frijters, P., & Shields, M. A. (2008). Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic literature*, *46*(1), 95-144. <https://doi.org/10.1257/jel.46.1.95>
- Cramer, A.O.J., Van Der Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S.H., Kendler, K.S., & Borsboom, D. (2012). Dimensions of Normal Personality as Networks in Search of Equilibrium: You Can't like Parties if you Don't like People. *European Journal of Personality*, *26*(4), 414–431. <https://doi.org/10.1002/per.1866>
- Cummins, R.A. (2000). Personal income and subjective well-being: A review. *Journal of happiness studies*, *1*(2), 133-158. <https://doi.org/10.1023/A:1010079728426>
- Cummins, R.A., Eckersley, R., Pallant, J., Van Vugt, J., & Misajon, R. (2003). Developing a national index of subjective wellbeing: The Australian Unity Wellbeing Index. *Social indicators research*, *64*(2), 159-190. <https://doi.org/10.1023/A:1024704320683>
- Deci, E. L., & Ryan, R. M. (2012). Self-determination theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (pp. 416–436). Sage Publications Ltd. <https://doi.org/10.4135/9781446249215.n21>
- de Vos, J. A., Radstaak, M., Bohlmeijer, E. T., & Westerhof, G. J. (2018). Having an eating disorder and still being able to flourish? Examination of pathological symptoms and well-being as two continua of mental health in a clinical sample. *Frontiers in psychology*, *9*, 2145. <https://doi.org/10.3389/fpsyg.2018.02145>
- de Vos, J. A., Radstaak, M., Bohlmeijer, E. T., & Westerhof, G. J. (2021). The psychometric network structure of mental health in eating disorder patients. *European Eating Disorders Review*, *29*(4), 559-574. <https://doi.org/10.1002/erv.2832>

- Diener, E. (1984). Subjective well-being. *Psychological bulletin*, 95(3), 542.
<https://doi.org/10.1037/0033-2909.95.3.542>
- Diener, E. (1995). A value based index for measuring national quality of life. *Social indicators research*, 36, 107-127. <https://doi.org/10.1007/BF01079721>
- Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological bulletin*, 125(2), 276.
<https://psycnet.apa.org/buy/1999-10106-007>
- Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American Psychologist*, 55(1), 34–43. <https://doi.org/10.1037/0003-066X.55.1.34>
- Diener, E., & Oishi, S. (2000). Money and happiness: Income and subjective well-being across nations. *Culture and subjective well-being*, 185, 218.
- Diener, E., & Biswas-Diener, R. (2002). Will money increase subjective well-being? *Social indicators research*, 57, 119-169. <https://doi.org/10.1023/A:1014411319119>
- Diener, E., & Suh, E.M. (2003). National differences in subjective well-being. In: D Kahneman, E Diener, N Schwarz. (eds.) *Well-Being: The foundations of hedonic psychology* (434–450). Russell Sage Foundation Publications.
- Diener, E., & Seligman, M.E. (2004). Beyond money. Toward an economy of well-being. *Psychological Science in the Public Interest*, 5(1):1–31.
- Diener, E., Lucas, R., Schimmack, U., & Helliwell, J. (2009). Well-Being for public policy. Oxford University Press.
<https://doi.org/10.1093/acprof:oso/9780195334074.001.0001>

- Diener, E., Lucas, R. E., & Oishi, S. (2018). Advances and open questions in the science of subjective well-being. *Collabra: Psychology*, 4(1).
<https://doi.org/10.1525/collabra.115>
- Easterlin, R. A. (2001). Income and happiness: Towards a unified theory. *The economic journal*, 111(473), 465-484. <https://doi.org/10.1111/1468-0297.00646>
- Epskamp, S., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of statistical software*, 48, 1-18. <https://doi.org/10.18637/jss.v048.i04>
- Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior research methods*, 50 (1), 195-212.
<https://doi.org/10.3758/s13428-017-0862-1>
- Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological methods*, 23(4), 617. <https://doi.org/10.1037/met0000167>
- Frederickson, B.L., & Levenson, R.W. (1998). Positive emotions speed recovery from the cardiovascular sequelae of negative emotions. *Cognition & emotion*, 12(2), 191-220. <https://doi.org/10.1080/026999398379718>
- Frey, B. & Stutzer, A. (2002). *Happiness and Economics: How the Economy and Institutions Affect Human Well-Being*. Princeton: Princeton University Press.
<https://doi.org/10.1515/9781400829262>
- Fried, E. I., Eidhof, M. B., Palic, S., Costantini, G., Huisman-van Dijk, H. M., Bockting, C. L. H., et al. (2018). Replicability and generalizability of posttraumatic stress disorder (PTSD) networks: a cross-cultural multisite study of PTSD symptoms in

four trauma patient samples. *Clin. Psychol. Sci.* 6, 335–351.

<https://doi.org/10.1177/2167702617745092>

Fujita, F., Diener, E., & Sandvik, E. (1991). Gender differences in negative affect and well-being: the case for emotional intensity. *Journal of personality and social psychology*, 61(3), 427. <https://doi.org/10.1037/0022-3514.61.3.427>

Ghadiri, A., Habermacher, A., & Peters, T. (2012). Four basic human needs at the heart of neuroscience. *Neuroleadership: A Journey Through the Brain for Business Leaders*, 69-83. https://doi.org/10.1007/978-3-642-30165-0_4

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2019). The German Socio-Economic Panel (SOEP). *Jahrbücher für Nationalökonomie und Statistik*, 239(2), 345-360. <https://doi.org/10.1515/jbnst-2018-0022>

Govorova, E., Benítez, I., & Muñoz, J. (2020). Predicting student well-being: Network analysis based on PISA 2018. *International Journal of Environmental Research and Public Health*, 17(11), 4014. <https://doi.org/10.3390/ijerph17114014>

Herzberg, P. Y., & Wildfang, S. (2018). Essstörungssymptome und Persönlichkeit: Implikationen für die Diagnostik aus einer Netzwerkperspektive. *Zeitschrift für Psychiatrie, Psychologie und Psychotherapie*. <https://doi.org/10.1024/1661-4747/a000355>

Heshmati, S., Oravec, Z., Brick, T. R., & Roeser, R. W. (2020). Assessing psychological well-being in early adulthood: Empirical evidence for the structure of daily well-being via network analysis. *Applied Developmental Science*, 26(2), 207-225. <https://doi.org/10.1080/10888691.2020.1766356>

- Hyde, J. S. (2005). The gender similarities hypothesis. *American psychologist*, *60*(6), 581.
<https://doi.org/10.1037/0003-066X.60.6.581>
- Hyde, J. S. (2007). New directions in the study of gender similarities and differences. *Current Directions in Psychological Science*, *16*(5), 259-263.
<https://doi.org/10.1111/j.1467-8721.2007.00516.x>
- Isvoranu, A. M., & Epskamp, S. (2021). Which estimation method to choose in network psychometrics? Deriving guidelines for applied researchers. *Psychological Methods*. Advance online publication. <https://doi.org/10.1037/met0000439>
- Jones, P. J. (2018). Networktools: Tools for identifying important nodes in networks. *R package version, 1*(0), 10-1155. <https://CRAN.R-project.org/package=networktools>
- Joshanloo, M., & Lamers, S. M. (2016). Reinvestigation of the factor structure of the MHC-SF in the Netherlands: Contributions of exploratory structural equation modeling. *Personality and individual differences*, *97*, 8-12.
<https://doi.org/10.1016/j.paid.2016.02.089>
- Joshanloo, M. (2016). Revisiting the empirical distinction between hedonic and eudaimonic aspects of well-being using exploratory structural equation modeling. *Journal of Happiness Studies*, *17*, 2023-2036.
<https://doi.org/10.1007/s10902-015-9683-z>
- Joshanloo, M., & Jovanović, V. (2017). The factor structure of the mental health continuum-short form (MHC-SF) in Serbia: An evaluation using exploratory structural equation modeling. *Journal of Mental Health*, *26*(6), 510-515.
<https://doi.org/10.1080/09638237.2016.1222058>

- Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the national academy of sciences*, *107*(38), 16489-16493. <https://doi.org/10.1073/pnas.101149210>
- Keyes, C. L. M. (1998). Social well-being. *Social Psychology Quarterly*, *61*(2), 121–140. <https://doi.org/10.2307/2787065>
- Keyes, C. L. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of health and social behavior*, 207-222. <https://doi.org/10.2307/3090197>
- Keyes, C. L. M. (2007). Promoting and protecting mental health as flourishing: a complementary strategy for improving national mental health. *American Psychologist*, *62*(2), 95-108. <https://doi.org/10.1037/0003-066X.62.2.95>
- Keyes, C. L., Wissing, M., Potgieter, J. P., Temane, M., Kruger, A., & Van Rooy, S. (2008). Evaluation of the Mental Health Continuum–Short Form (MHC–SF) in setswana-speaking South Africans. *Clinical psychology & psychotherapy*, *15*(3), 181-192. <https://doi.org/10.1002/cpp.572>
- Lambert, L., Passmore, H.-A., & Holder, M. D. (2015). Foundational frameworks of positive psychology: Mapping well-being orientations. *Canadian Psychology / Psychologie canadienne*, *56*(3), 311–321. <https://doi.org/10.1037/cap0000033>
- Lamers, S. M. A., Westerhof, G. J., Bohlmeijer, E. T., Ten Klooster, P. M., & Keyes, C. L. M. (2011). Evaluating the psychometric properties of the mental health continuum-short form (MHC-SF). *Journal of Clinical Psychology*, *67*(1), 99– 110. <https://doi.org/10.1002/jclp.20741>
- Linton, M. J., Dieppe, P., & Medina-Lara, A. (2016). Review of 99 self-report measures for assessing well-being in adults: exploring dimensions of well-being and

developments over time. *BMJ open*, 6(7), e010641.

<http://dx.doi.org/10.1136/bmjopen-2015-010641>

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect:

Does happiness lead to success? *Psychological Bulletin*, 131 (6):803–855.

<https://doi.org/10.1037/0033-2909.131.6.803>

Nisbett, R. E. (2019). Cognition and perception: East and West. In *Progress in*

Psychological Science around the World (pp. 209-228). Routledge.

<https://doi.org/10.4324/9781315793184>

Orth, U., & Robins, R. W. (2014). The development of self-esteem. *Current directions in psychological science*, 23(5), 381-387. <https://doi.org/10.1177/0963721414547414>

Rogoza, R., Truong Thi, K. H., Różycka-Tran, J., Piotrowski, J., & Żemojtel-Piotrowska, M. (2018). Psychometric properties of the MHC-SF: An integration of the existing measurement approaches. *Journal of Clinical Psychology*, 74(10), 1742-1758.

<https://doi.org/10.1002/jclp.22626>

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual review of psychology*,

52(1), 141-166. <https://doi.org/10.1146/annurev.psych.52.1.141>

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Publications.

Ryff, C. D., & Keyes, C. L. M. (1995). The structure of psychological well-being revisited.

Journal of Personality and Social Psychology, 69, 719–727.

<https://doi.org/10.1037/0022-3514.69.4.719>

- Ryff, C. D. (2013). Psychological well-being revisited: Advances in the science and practice of eudaimonia. *Psychotherapy and psychosomatics*, 83(1), 10-28.
<https://doi.org/10.1159/000353263>
- Ryff, C. D. (2014). Self-realisation and meaning making in the face of adversity: A eudaimonic approach to human resilience. *Journal of psychology in Africa*, 24(1), 1-12. <https://doi.org/10.1080/14330237.2014.904098>
- Seligman, M. E., & Csikszentmihalyi, M. (2000). *Positive psychology: An introduction* (Vol. 55, No. 1, p. 5). American Psychological Association.
<https://doi.org/10.1037/0003-066X.55.1.5>
- Sheldon, K. M., & Lyubomirsky, S. (2006). How to increase and sustain positive emotion: The effects of expressing gratitude and visualizing best possible selves. *The journal of positive psychology*, 1(2), 73-82. <https://doi.org/10.1080/17439760500510676>
- Stangl, W. (2023, June 2). *Easterlin-Paradox – Online Lexikon für Psychologie & Pädagogik*. <https://lexikon.stangl.eu/12898/easterlin-paradox>.
- Stevenson, B., & Wolfers, J. (2009). The paradox of declining female happiness. *American Economic Journal: Economic Policy*, 1(2), 190-225.
<https://doi.org/10.1257/pol.1.2.190>
- Sun, S., Chen, J., Johannesson, M., Kind, P., & Burström, K. (2016). Subjective well-being and its association with subjective health status, age, sex, region, and socio-economic characteristics in a Chinese population study. *Journal of Happiness Studies*, 17, 833-873. <https://doi.org/10.1007/s10902-014-9611-7>
- van Borkulo, C., Boschloo, L., Borsboom, D., Penninx, B. W., Waldorp, L. J., and Schoevers, R. A. (2015). Association of symptom network structure with the course

of depression. *JAMA Psychiat.* 72, 1219–1226.

<https://doi.org/10.1001/jamapsychiatry.2015.2079>

van Borkulo, C. (2016). Network Comparison Test. Retrieved from:

<https://github.com/cvborkulo/NetworkComparisonTest>

van Borkulo, C. (2018). A tutorial on R package NetworkComparisonTest (NCT).

Symptom network models in depression research: From methodological exploration to clinical application, 249-57.

van de Weijer, M., Landvreugd, A., Pelt, D., & Bartels, M. (2021). Connecting the dots:

Using a network approach to study the well-being spectrum. PsyArXiv.

<https://doi.org/10.31234/osf.io/9u6vt>

Warr, P. (2003). Well-being in the workplace. In: D Kahneman , E Diener, N Schwarz

(eds.) *Well-Being: The foundations of hedonic psychology* (pp. 392–412). Russell Sage Foundation Publications.

Wasil, A. R., Gillespie, S., Park, S. J., Venturo-Conerly, K. E., Osborn, T. L., DeRubeis, R.

J., ... & Jones, P. J. (2021). Which symptoms of depression and anxiety are most strongly associated with happiness? A network analysis of Indian and Kenyan adolescents. *Journal of Affective Disorders*, 295, 811-821.

<https://doi.org/10.1016/j.jad.2021.08.087>

Westerhof, G. J., & Keyes, C. L. (2010). Mental illness and mental health: The two

continua model across the lifespan. *Journal of adult development*, 17(2), 110-119.

<https://doi.org/10.1007/s10804-009-9082-y>

World Health Organization. (2022, Oct 19). *Mental health: a state of well-being*.

http://www.who.int/feature/factfiles/mental_health/en/

- Xiao, Z. D., Baranski, E., & Funder, D. (2016). The Where of Happiness: Cross-Cultural Comparison of Happiness and Situational Experience. *Undergraduate Research Journal*, 55. https://engage.ucr.edu/sites/default/files/2019-04/VOL%20X_0.pdf#page=56
- Zanon, C., Fabretti, R. R., Martins, J. Z., & Heath, P. J. (2022). Adaptation of the Steen Happiness Index (SHI) to Brazil: A comparison of the psychometric properties of the SHI and the Subjective Happiness Scale. *Assessment*, 29(8), 1597-1610. <https://doi.org/10.1177/10731911211024354>
- Zeng, G., Peng, K., & Hu, C. P. (2019). The network structure of adolescent well-being traits: results from a large-scale Chinese sample. *Frontiers in psychology*, 10, 2783. <https://doi.org/10.3389/fpsyg.2019.02783>
- Ziegler, P. (2020). *Subjektives Wohlbefinden von Studierenden-Einflussfaktoren auf das subjektive Wohlbefinden und Zusammenhänge mit der Studienabbruchsinention* (Doctoral dissertation, Universität Passau).

Appendix

Appendix A: Tables and Figures

Table A1

Partial Correlations among all MHC-SF items for whole Sample

	HAP	INT	LFS	SCN	SIN	SAC	SCC	SOC	SEA	MAS	PRL	PGO	AUT	PUL
HAP	0,00	0,25	0,49	0,00	0,00	0,10	0,00	-0,12	0,07	-0,08	0,20	0,00	0,00	0,12
INT		0,00	0,22	0,10	0,00	0,00	0,07	0,09	0,00	0,10	0,00	0,00	0,00	0,15
LFS			0,00	0,08	0,00	0,00	0,00	0,00	0,00	0,14	0,00	-0,10	0,00	0,00
SCN				0,00	0,32	0,16	0,00	0,00	0,00	0,00	0,00	0,10	0,00	0,12
SIN					0,00	0,10	0,00	0,00	0,00	0,00	0,12	0,00	0,00	0,00
SAC						0,00	0,35	0,17	0,10	-0,10	-0,10	0,11	0,00	0,00
SCC							0,00	0,18	0,08	0,00	0,09	0,00	0,00	0,00
SOC								0,00	0,18	0,11	0,00	0,12	0,08	-0,07
SEA									0,00	0,34	0,00	0,10	0,11	0,09
MAS										0,00	0,15	-0,19	0,10	0,18
PRL											0,00	0,17	0,16	0,09
PGO												0,00	0,22	0,17
AUT													0,00	0,22
PUL														0,00

Note. HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SOC=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A2*Partial Correlations among all MHC-SF items for female sample*

	HAP	INT	LFS	SCN	SIN	SAC	SCC	SOC	SEA	MAS	PRL	PGO	AUT	PUL
HAP	0,00	0,24	0,47	0,00	0,00	0,00	0,00	-0,11	0,00	0,00	0,19	0,00	0,00	0,11
INT		0,00	0,28	0,11	0,00	0,00	0,00	0,08	0,00	0,09	0,00	0,00	0,00	0,15
LFS			0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,00	-0,11	0,00	0,00
SCN				0,00	0,31	0,15	0,00	0,00	0,09	0,00	0,00	0,00	0,00	0,00
SIN					0,00	0,11	0,00	0,00	0,00	0,00	0,10	0,00	0,00	0,09
SAC						0,00	0,35	0,19	0,00	0,00	0,00	0,10	0,00	0,00
SCC							0,00	0,21	0,11	0,00	0,00	0,00	0,00	0,00
SOC								0,00	0,18	0,00	0,00	0,16	0,00	0,00
SEA									0,00	0,35	0,00	0,00	0,14	0,09
MAS										0,00	0,13	-0,14	0,00	0,21
PRL											0,00	0,14	0,16	0,08
PGO												0,00	0,22	0,19
AUT													0,00	0,19
PUL														0,00

Note. HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SOC=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A3*Partial Correlations among all MHC-SF items for male sample*

	HAP	INT	LFS	SCN	SIN	SAC	SCC	SOC	SEA	MAS	PRL	PGO	AUT	PUL
HAP	0,00	0,26	0,50	0,00	0,00	0,13	0,00	-0,13	0,12	0,00	0,20	0,00	-0,07	0,12
INT		0,00	0,17	0,00	0,00	0,00	0,12	0,00	0,00	0,10	0,00	0,00	0,00	0,14
LFS			0,00	0,10	0,00	0,00	0,00	0,00	-0,09	0,17	0,08	0,00	0,00	0,00
SCN				0,00	0,33	0,17	0,00	0,00	0,00	0,00	0,00	0,15	0,00	0,16
SIN					0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00
SAC						0,00	0,33	0,14	0,14	-0,13	0,00	0,13	0,00	0,00
SCC							0,00	0,18	0,00	0,00	0,00	0,00	0,00	0,00
SOC								0,00	0,19	0,19	0,00	0,00	0,09	0,00
SEA									0,00	0,32	0,00	0,13	0,09	0,10
MAS										0,00	0,16	-0,20	0,13	0,12
PRL											0,00	0,18	0,18	0,10
PGO												0,00	0,22	0,12
AUT													0,00	0,24
PUL														0,00

Note. HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SOC=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A4*Partial Correlations among all MHC-SF items for low income sample*

	HAP	INT	LFS	SCN	SIN	SAC	SCC	SOC	SEA	MAS	PRL	PGO	AUT	PUL
HAP	0,00	0,24	0,49	0,00	0,00	0,09	0,00	-0,14	0,00	0,00	0,16	0,00	0,00	0,09
INT		0,00	0,26	0,09	0,00	-0,11	0,00	0,11	0,00	0,08	0,00	0,00	0,00	0,18
LFS			0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,10	0,08	-0,14	0,00	0,00
SCN				0,00	0,29	0,17	0,00	0,00	0,00	0,00	0,00	0,11	0,00	0,00
SIN					0,00	0,12	0,00	0,00	0,00	0,00	0,14	0,00	0,00	0,00
SAC						0,00	0,34	0,16	0,00	0,00	0,00	0,00	0,00	0,00
SCC							0,00	0,19	0,00	0,00	0,00	0,00	0,00	0,00
SOC								0,00	0,23	0,00	0,00	0,17	0,00	0,00
SEA									0,00	0,32	0,00	0,00	0,00	0,14
MAS										0,00	0,22	-0,25	0,00	0,19
PRL											0,00	0,18	0,20	0,00
PGO												0,00	0,19	0,19
AUT													0,00	0,24
PUL														0,00

Note. HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SOC=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A5*Partial Correlations among all MHC-SF items for middle income sample*

	HAP	INT	LFS	SCN	SIN	SAC	SCC	SOC	SEA	MAS	PRL	PGO	AUT	PUL
HAP	0,00	0,18	0,51	0,00	0,00	0,11	0,00	-0,08	0,07	-0,11	0,28	0,00	0,00	0,14
INT		0,00	0,26	0,00	0,11	0,00	0,00	0,00	0,00	0,15	0,00	0,00	0,00	0,09
LFS			0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00
SCN				0,00	0,35	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13
SIN					0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
SAC						0,00	0,37	0,18	0,11	-0,21	-0,16	0,15	0,00	0,00
SCC							0,00	0,14	0,00	0,10	0,14	0,00	0,00	0,00
SOC								0,00	0,18	0,17	0,00	0,00	0,00	0,00
SEA									0,00	0,31	0,00	0,17	0,15	0,00
MAS										0,00	0,00	0,00	0,12	0,21
PRL											0,00	0,22	0,14	0,11
PGO												0,00	0,21	0,10
AUT													0,00	0,20
PUL														0,00

Note. HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SOC=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A6

Partial Correlation Coefficients per Edge in Female and Male Group that Differ Significantly and p-values

Edge1 - Edge2	female	male	p-value
	r	r	
INT - LFS	.28	.17	≤ .05
INT - SCC	.00	.12	≤ .05
HAP - SEA	.00	.12	≤ .05
LFS - SEA	.00	-.09	< .01
SCO - MAS	.00	.19	< .01
HAP - AUT	.00	-.07	≤ .05
SIN - PUL	.09	.00	< .01

Note. Edge = correlation between two different nodes. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Table A7

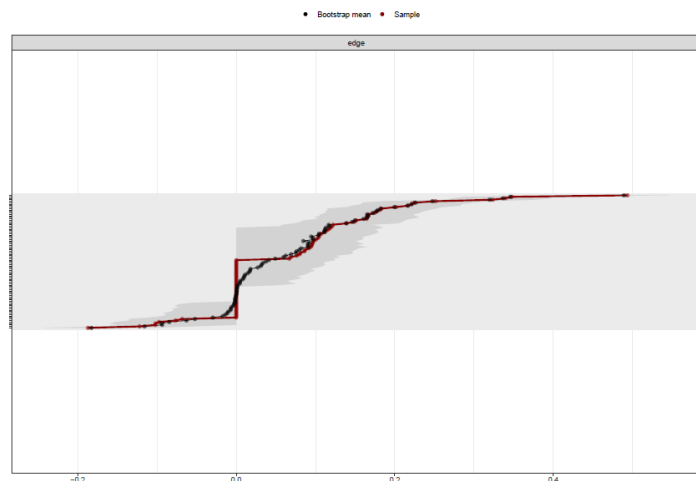
Partial Correlation Coefficients per Edge in Income Groups that Differ Significantly and p-values

Edge1 – Edge2	income group		p-value
	low	middle	
	r	r	
HAP - MAS	0,00	-0,11	< .01
INT - SIN	0,00	0,11	≤ .05
INT - SAC	-0,11	0,00	< .01
SAC - MAS	0,00	-0,21	< .01
SOC - MAS	0,00	0,17	≤ .05
MAS - PRL	0,22	0,00	≤ .05
MAS - PGO	-0,25	0,00	< .01

Note. Edge = correlation between two different nodes. The items presented in the order of the Mental Health Continuum- Short Form are: HAP=happiness, INT=interest, LFS=life satisfaction, SCN=social contribution, SIN=social integration, SAC=social actualization, SCC=social acceptance, SCO=social coherence, SEA=self-acceptance, MAS=mastery, PRL=positive relations, PGO=personal growth, AUT=autonomy, PUL=purpose in life.

Figure A1

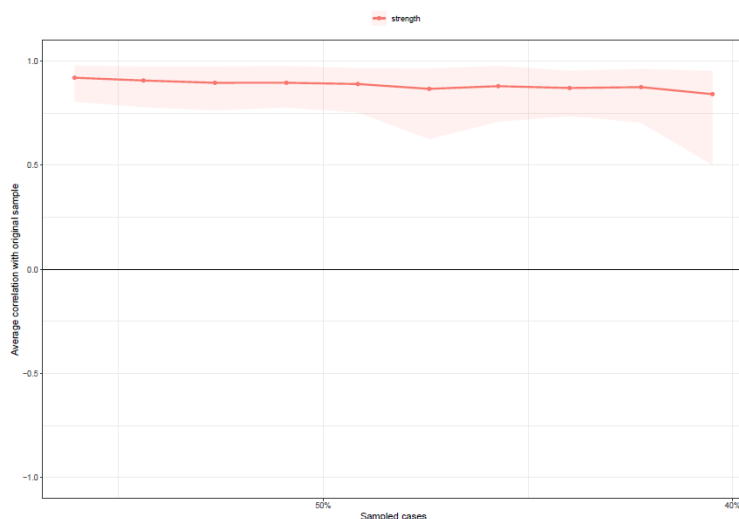
Bootstrapped Confidence Intervals of Estimated Edge weights for the Estimated Network of the whole Sample



Note. The red line indicates the sample values and the grey area the bootstrapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge weight to the edge with the lowest edge weight. The y axis labels have been removed to avoid cluttering. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A2

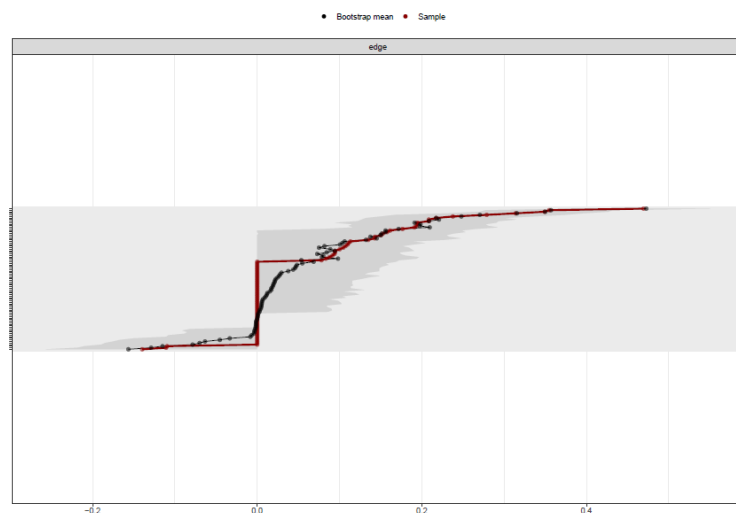
Robustness of the Centrality Measures of the whole Sample Network



Note. Robustness of the 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. If the correlation is strong after dropping a high percentage of participants, the original network's centrality measures can be considered robust.

Figure A3

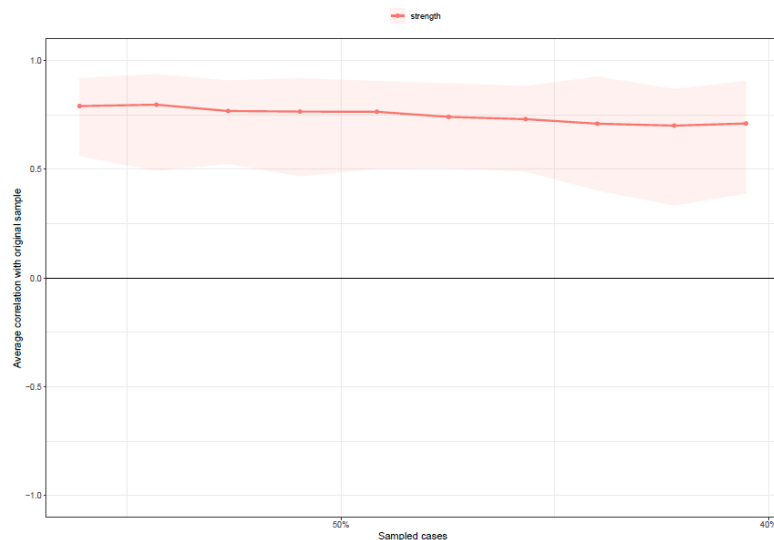
Bootstrapped Confidence Intervals of Estimated Edge Weights for the Estimated Network of the Female Group



Note. The red line indicates the sample values and the grey area the bootstrapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge weight to the edge with the lowest edge weight. The y axis labels have been removed to avoid cluttering. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A4

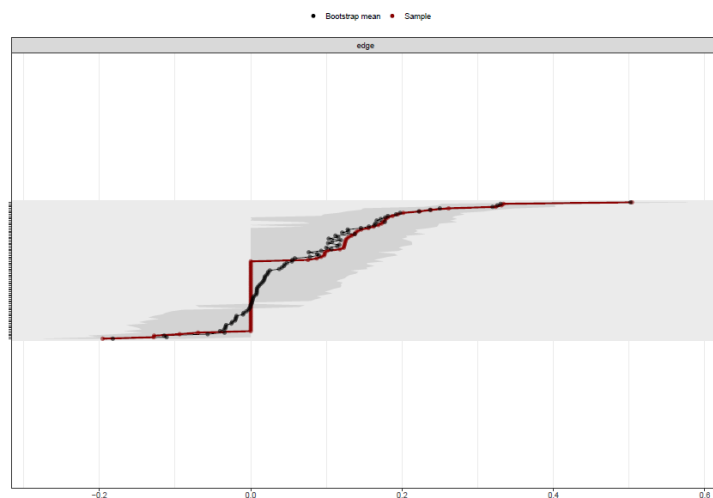
Robustness of the Centrality Measures of the Female Network



Note. Robustness of the 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. If the correlation is strong after dropping a high percentage of participants, the original network's centrality measures can be considered robust.

Figure A5

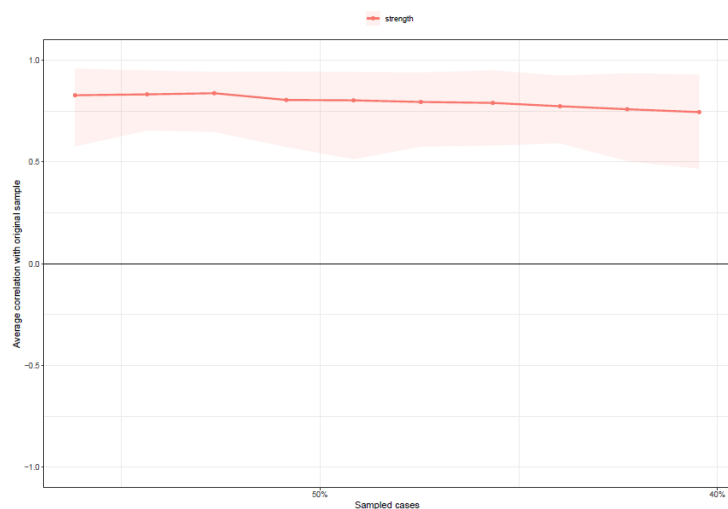
Bootstrapped Confidence Intervals of Estimated Edge Weights for the Estimated Network of the Male Group



Note. The red line indicates the sample values and the grey area the bootstrapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge weight to the edge with the lowest edge weight. The y axis labels have been removed to avoid cluttering. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A6

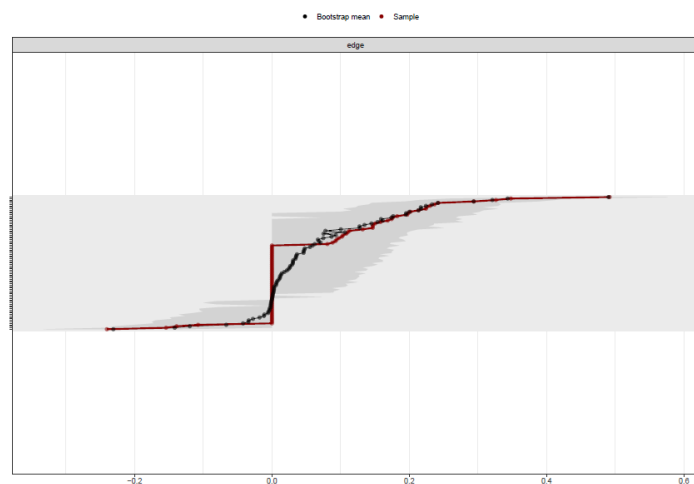
Robustness of the Centrality Measures of the Male Network



Note. Robustness of the 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. If the correlation is strong after dropping a high percentage of participants, the original network's centrality measures can be considered robust.

Figure A7

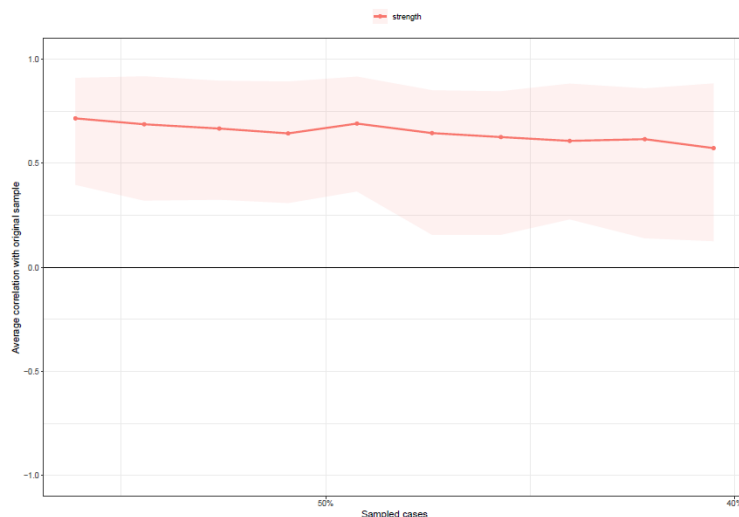
Bootstrapped Confidence Intervals of Estimated Edge Weights for the Estimated Network of the Low Income group



Note. The red line indicates the sample values and the grey area the bootstrapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge weight to the edge with the lowest edge weight. The y axis labels have been removed to avoid cluttering. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A8

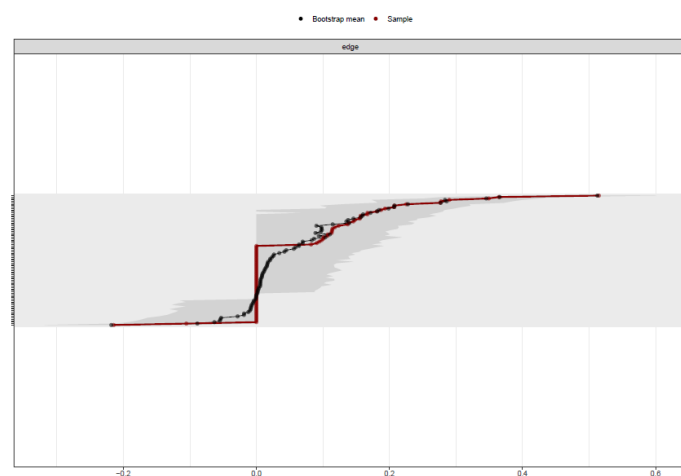
Robustness of the Centrality Measures of the Low Income Network



Note. Robustness of the 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. If the correlation is strong after dropping a high percentage of participants, the original network's centrality measures can be considered robust.

Figure A9

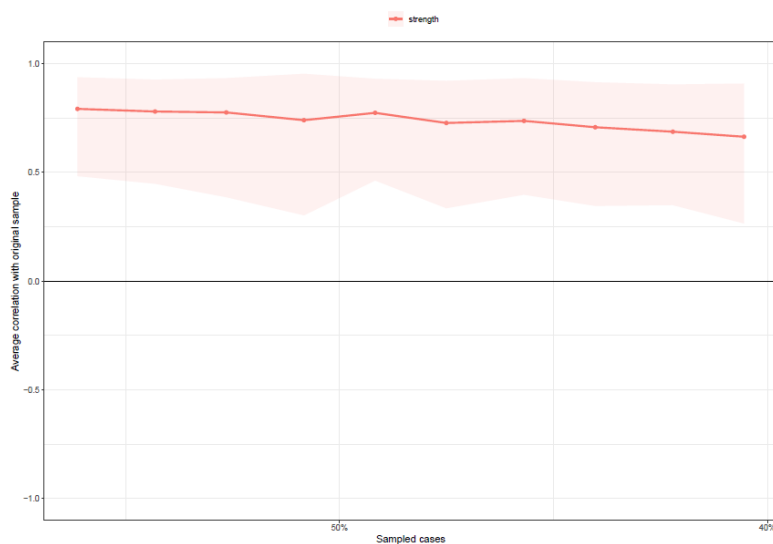
Bootstrapped Confidence Intervals of Estimated Edge Weights for the Estimated Network of the Middle Income group



Note. The red line indicates the sample values and the grey area the bootstrapped CIs. Each horizontal line represents one edge of the network, ordered from the edge with the highest edge weight to the edge with the lowest edge weight. The y axis labels have been removed to avoid cluttering. Narrower CIs are the more steady and robust estimation of the edge weights.

Figure A10

Robustness of the Centrality Measures of the Middle Income Network



Note. Robustness of the 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. If the correlation is strong after dropping a high percentage of participants, the original network's centrality measures can be considered robust.

... that your life has a sense of direction or meaning to it?	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
--	--------------------------	--------------------------	--------------------------	--------------------------	--------------------------	--------------------------

Appendix B: R Code

```
##load packages

rm(list= ls())

install.packages("qgraph")

install.packages("bootnet")

install.packages("mgm")

install.packages("tidyverse")

install.packages("foreign")

install.packages("psych")

install.packages("EGAnet")

install.packages("ggpubr")

install.packages("ggplot2")

install.packages("haven")

install.packages("sna")

install.packages("summarytools")

install.packages("NetworkComparisonTest")

install.packages("ltm")

install.packages("networktools")

install.packages("summariser")

install.packages("openxlsx")

library(foreign)

library(psych)

library(EGAnet)

library(ggpubr)

library(ggplot2)

library(qgraph)

library(bootnet)

library(mgm)
```



```
library(tidyverse)
library(haven)
library(sna)
library(summarytools)
library(NetworkComparisonTest)
library(ltm)
library(networktools)
library(summariser)
library(psych)
library(summarytools)
library(haven)
library(qgraph)
library(bootnet)
library(NetworkComparisonTest)
library(networktools)
library(openxlsx)

##change name of Items
names(mess)[names(mess) == "MHC01"] <- "HAP"
names(mess)[names(mess) == "MHC02"] <- "INT"
names(mess)[names(mess) == "MHC03"] <- "LFS"
names(mess)[names(mess) == "MHC04"] <- "SCN"
names(mess)[names(mess) == "MHC05"] <- "SIN"
names(mess)[names(mess) == "MHC06"] <- "SAC"
names(mess)[names(mess) == "MHC07"] <- "SCC"
names(mess)[names(mess) == "MHC08"] <- "SOC"
names(mess)[names(mess) == "MHC09"] <- "SEA"
```

```

names(mess)[names(mess) == "MHC10"] <- "MAS"
names(mess)[names(mess) == "MHC11"] <- "PRL"
names(mess)[names(mess) == "MHC12"] <- "PGO"
names(mess)[names(mess) == "MHC13"] <- "AUT"
names(mess)[names(mess) == "MHC14"] <- "PUL"

##create wellbeing data

wellbeing <- c("HAP", "INT", "LFS", "SCN", "SIN", "SAC", "SCC", "SOC",
"SEA", "MAS", "PRL", "PGO",
"    "AUT", "PUL" )

newdata <- mess[wellbeing]

##exclude unnecessary variables

excl_vars <- names(mess[c(1:10,12,13,15:22,24:49,64:96)])

tidydataset <- mess[,!(names(mess)%in%excl_vars)]

##goldbricker function to identify redundant nodes

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

##catagorize income

data_noinfo <- subset(tidydataset, nettoink <1)
data_lowincome <- subset(tidydataset, nettoink>0 & nettoink<1447)
data_middleincome <- subset(tidydataset, nettoink>1447 & nettoink<3100)
data_highincome <- subset(tidydataset, nettoink>3100 & nettoink<300000)

```

```
##create subsample male participants
malepart <- tidydataset
malepart <- subset(malepart, geschlecht==1)
excl_male <- names(malepart[c(1:3)])
malepart <- malepart[,!(names(malepart)%in%excl_male)]

##create subsample female participants
femalepart <- tidydataset
femalepart <- subset(femalepart, geschlecht==2)
excl_female <- names(femalepart[c(1:3)])
femalepart <- femalepart[,!(names(femalepart)%in%excl_female)]

##create subsample low income
lowincome <- data_lowincome
lowincome <- subset(lowincome, nettoink>0 & nettoink<1447)
excl_lowincome <- names(lowincome[c(1:3)])
lowincome <- lowincome[,!(names(lowincome)%in%excl_lowincome)]

##create subsample middle income
middleincome <- data_middleincome
middleincome <- subset(middleincome, nettoink>1447 & nettoink<3100)
excl_middleincome <- names(middleincome[c(1:3)])
middleincome <- middleincome[,!(names(middleincome)%in%excl_middleincome)]

##create subsample high income
highincome <- data_highincome
highincome <- subset(highincome, nettoink>3100 & nettoink<300000)
```

```

excl_highincome <- names(highincome[c(1:3)])

highincome <- highincome[,!(names(highincome)%in%excl_highincome)]

##form the domains of MHC

group <- list(c(1:3), c(4:8), c(9:14))

names(group)=c('EWB','SWB', 'PWB')

##estimate network of well-being for the entire sample

set.seed(1)

everyone_network <- qgraph(input = cor_auto(newdata), groups=group, layout = 'spring',
graph = "EBICglasso", legend = TRUE, sampleSize = nrow(newdata), threshold = TRUE,
filetype = ".png", esize = 10, color=c("lightgreen", "orange", 'red'))

##calculate partial correlations for the network

myedges <- getWmat(everyone_network)

##estimate network of well-being for males

set.seed(1)

male_network <- qgraph(input = cor_auto(malepart), groups=group, layout = "spring",
graph = "EBICglasso", legend = FALSE, sampleSize = nrow(malepart), threshold =
TRUE, filetype = ".png", esize = 10, color=c("lightgreen", "orange", 'red'))

##estimate network of well-being for females

set.seed(1)

female_network <- qgraph(input = cor_auto(femalepart), groups=group, layout =
LayoutM, graph = "EBICglasso", legend = FALSE, sampleSize = nrow(femalepart),
threshold = TRUE, filetype = ".png", esize = 10, color=c("lightgreen", "orange", 'red'))

##estimate network of well-being for the lowincome sample

set.seed(1)

```

```
lowincome_network <- qgraph(input = cor_auto(lowincome), groups=group, layout =
'spring', graph = "EBICglasso", legend = FALSE, sampleSize = nrow(lowincome),
threshold = TRUE, filetype = ".png", esize = 10, color=c("lightgreen", "orange", 'red'))
```

```
Layoutl <- averageLayout(lowincome_network)
```

```
##estimate network of well-being for the middleincome sample
```

```
set.seed(1)
```

```
middleincome_network <- qgraph(input = cor_auto(middleincome), groups=group, layout
= Layoutl, graph = "EBICglasso", legend = FALSE, sampleSize = nrow(middleincome),
threshold = TRUE, filetype = ".png", esize = 10, color=c("lightgreen", "orange", 'red'))
```

```
##calculate partial correlations
```

```
myedges_low <- getWmat(lowincome_network)
```

```
myedges_middle <- getWmat(middleincome_network)
```

```
myedges_female <- getWmat(female_network)
```

```
myedges_male <- getWmat(male_network)
```

```
##centrality estimates (plots) for whole sample
```

```
centralityPlot((everyone_network), include = "Strength", orderBy="Strength", scale = 'z-
scores')
```

```
##centrality estimates (plots) for male and female groups
```

```
centralityPlot(list(Male=male_network, Female=female_network), include = "Strength",
orderBy = "Strength", scale = 'z-scores')
```

```
##centrality estimates (plots) for low- and middle-income groups
```

```
centralityPlot(list(low=lowincome_network, middle=middleincome_network), include =
"Strength", orderBy = "Strength", scale = 'z-scores')
```

```
##stability analysis of the entire sample
```

```
set.seed(123)
```

```
everyone_NW <- estimateNetwork(newdata, corMethod = "cor_auto", default =  
"EBICglasso", threshold = TRUE) #hier wird nochmal das netzwerk erstellt, habe ich zwar  
schon, aber anders geht es nicht
```

```
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
```

```
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

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 = 0.0, caseMax = 0.439)

corStability(boot_female2, cor = 0.7, statistics = "strength", verbose = TRUE)

print(boot_female2)

plot(boot_female2)

##stability analysis of low income group

set.seed(123)

lowincome_NW <- estimateNetwork(lowincome, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)
```

```
set.seed(123)

boot_lowincome <- bootnet(lowincome_NW, statistics = "edge", nBoots = 1000, nCores =
4)

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

summary(boot_lowincome)

print(boot_lowincome)
```

```
set.seed(123)

boot_lowincome2 <- bootnet(lowincome_NW, statistics = "strength", nBoots = 1000, type
= "case", nCores = 4, caseMin = 0.0, caseMax = 0.439)

corStability(boot_lowincome2, cor = 0.7, statistics = "strength", verbose = TRUE)

print(boot_lowincome2)

plot(boot_lowincome2)
```

##stability analysis of middle income group

```
set.seed(123)

middleincome_NW <- estimateNetwork(middleincome, corMethod = "cor_auto", default =
"EBICglasso", threshold = TRUE)
```

```
set.seed(123)

boot_middleincome <- bootnet(middleincome_NW, statistics = "edge", nBoots = 1000,
nCores = 4)

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

summary(boot_middleincome)

print(boot_middleincome)
```

```
set.seed(123)
```



```

boot_middleincome2 <- bootnet(middleincome_NW, statistics = "strength", nBoots =
1000, type = "case", nCores = 4, caseMin = 0.0, caseMax = 0.439)

corStability(boot_middleincome2, cor = 0.7, statistics = "strength", verbose = TRUE)

print(boot_middleincome2)

plot(boot_middleincome2)

##compare networks of male and female groups

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.centralities = TRUE, centralities = "strength", nodes = "all")

summary(malefemale)

print(malefemale)

##compare networks of low and middle income groups

set.seed(123)

low_middle_NW <- NetworkComparisonTest::NCT(lowincome_NW, middleincome_NW,
it = 20, binary.data = FALSE, paired = FALSE, test.edges = TRUE, edges = "all",
progressbar = TRUE, test.centralities = TRUE, centralities = "strength", nodes = "all")

summary(low_middle_NW)

print(low_middle_NW)

##Cronbach's alpha

mess <- mess[50:63]

cronbach.alpha(mess) #Cronbach's alpha for all 3 Dimensions

messemotional <- mess[1:3]

cronbach.alpha(messemotional) #Cronbach's alpha for EWB

```

```
messsocial <- mess[4:8]
```

```
cronbach.alpha(messsocial) #Cronbach's alpha for SWB
```

```
messpsychological <- mess[9:14]
```

```
cronbach.alpha(messpsychological) #Cronbach's alpha for PWB
```

```
##see summary of the data
```

```
View(dfSummary(tidydataset))
```

