

Connecting the dots: Using a network approach to study the well-being spectrum

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Abstract

Many theories on the structure of well-being exist, but there is no consensus on how different well-being constructs fit into an overarching well-being framework. We sought insight into the structure of well-being using a psychometric network approach in a sample of Netherlands Twin Register participants. First, in a trimming sample of $N=1343$ participants, we examine potential item redundancy based on associations between satisfaction with life, subjective happiness, quality of life, flourishing, self-rated health, depressive symptoms, neuroticism, and loneliness items. Next, we fit the network in a estimation sample of $N=759$ participants, and examine the performance and accuracy of the network. Our final network consists of a positive cluster including satisfaction with life, subjective happiness, and flourishing items, and a negative cluster including depressive symptoms, loneliness, and neuroticism items. While items belonging to the same well-being measure clustered together, all well-being items were densely connected, re-affirming the complexity of the construct.

Key words: well-being, depression, network, flourishing, happiness.

Introduction

Defining and delineating well-being as a construct has proven to be one of the more difficult challenges for the field of positive psychology. There are many different well-being theories, and it is often unclear how these different theories relate to or complement each other. Well-being seems to be an umbrella term for many different more or less connected constructs, which can lead to difficulties when interpreting and comparing the results from positive psychological research (Linton et al., 2016).

Various researchers have made an effort to outline different well-being theories based on existing research (for examples, see: Deci & Ryan, 2008; Diener & Ryan, 2009; Lambert et al., 2015). While it is beyond the scope of the present study to review all existing theories, we will provide a brief overview of some of the main theories and their origins. Most of the existing positive psychological theories on well-being originate from philosophical traditions. Lambert, Passmore & Holder distinguish four (partly overlapping) philosophical traditions that were influential for well-being research: utilitarianism (focus on community well-being and maximizing happiness), virtue philosophy (focus on character strengths), hedonism (focus on maximizing pleasure), and eudaimonism (focus on functioning well and meaning) (Lambert et al., 2015). An influential contemporary well-being theory combining aspects of all four of these traditions is PERMA (Seligman, 2011). The theory postulates that Positive Emotion, Engagement, Relationships, Meaning and Accomplishment (PERMA) are the building blocks of well-being. While the different PERMA elements correlate with each other (Goodman et al., 2017), they are believed to also independently contribute to overall well-being and can be measured and defined independently using the PERMA profiler (Seligman, 2018).

Instead of combining elements from different philosophical traditions, most contemporary well-being theories tend to focus on a specific tradition. For example, Diener's theory on subjective well-being (SWB) is grounded in the hedonistic tradition of well-being and proposes that SWB is comprised of life satisfaction (cognitive SWB), high levels of positive affect, and low levels of negative affect (emotional SWB) (Diener, 1984). On the other hand, Ryff's theory on psychological well-being (PWB) is grounded in the eudaimonic tradition of well-being and states that PWB is comprised of six dimensions: autonomy, environmental mastery, personal growth, positive relationships, purpose in life, and self-acceptance (Ryff, 1989). A similar influential theory is self-determination theory (SDT) (Ryan & Deci, 2000). Central to SDT is an individual's experience of autonomy, competence, and relatedness, which are argued to promote well-being. This is slightly different from Ryff's PWB theory, where these dimensions are believed to be components of well-being. Combining aspects from both eudaimonic and hedonic theory, Keyes formulated a theory on flourishing that posits that well-being or mental health is defined by high levels of emotional, psychological, and social well-being, and an absence of psychopathy (Keyes, 2005). The inclusion of social well-being is in line with eudaimonic ideology and is well-supported by well-being literature (Keyes, 1998). While all the aforementioned theories focus on specific aspects of well-being, it is also possible to evaluate well-being in a broader context. Well-being is highly (phenotypically and genetically) correlated to multiple traits, such as depression, neuroticism, loneliness and self-rated health. In previous research, these traits were collectively referred to as "the well-being spectrum" (WBS) (Baselmans et al., 2019).

Importantly, these theories do not necessarily claim to provide a comprehensive well-being framework encompassing the well-being construct in its entirety. At the same time, it is not clear how these different theories combine into one framework: it is unlikely they are all

touching upon completely separate domains of the same overarching construct, but it is also unclear to what extent the different well-being constructs overlap. The most common way in which this issue has been studied is through factor analytical methods. In these models, item responses are modelled so that they “load” onto higher-order well-being factors such as SWB and PWB, and the relation between these higher order factors is evaluated by correlating them with each other. These studies provide mixed results, with some studies finding single factor solutions (Kim et al., 2016), and some finding multiple-factor solutions with varying degrees of correlations between these factors (Joshi, 2016; McMahan & Estes, 2011; Vanhoute & Nazroo, 2014). Factor analytical methods implicitly assume a top-down (reflective) model in which correlations between indicators are explained by the latent factor. This means that they assume that conditional on the latent factor, correlations between the items are zero. Consequently, information on the relations between the different items, independent from them loading on the same higher-order factors, is mostly lost. However, some authors claim that well-being is a bottom-up (formative) construct in which, for example, positive feelings, absence of negative feelings and life satisfaction together aggregate to feelings of well-being (Busseri & Sadava, 2010). Such models do not make assumptions about the correlations between indicators. By modeling well-being items as part of an overarching construct, we risk losing important information on the relation between these different components at an item level.

An alternative, less commonly employed, approach to studying (associations between) psychological traits is psychometric network analysis. A network consists of a set of nodes along with a set of specified ties (edges) linking the nodes (Borgatti & Halgin, 2011; Sacha Epskamp, Borsboom, et al., 2018). Characterizing the structure of networks and the position of nodes, and using these networks to better understand the examined phenotype, is what network scientists aim to achieve. There are three main advantages of using the network

approach as opposed to factor analysis or estimating regular correlations between traits. First, network analysis provides us with a means to easily and clearly explore all the possible associations between items. The network approach is agnostic about whether in reality well-being is characterized by top-down or bottom-up processes; it simply characterizes the (partial) correlation structure among a set of indicators. The second advantage is that the associations found in a network are a better indicator of causal relationships between items than regular correlation estimates (Epskamp & Fried, 2018). This is because the correlations in the network are partial correlations between items that remain when relationships with all other items are controlled for. The third advantage is the clinical and societal relevance of applying the network approach. The network can reveal which components are the most relevant using the concept of centrality: components with a high degree of centrality strongly affect the other components (items) in a network, because they are most strongly connected to other items (Fried et al., 2017). This source of information can help to decide on which component and paths to focus on during prevention or intervention. Components that are central to the network (i.e., high levels of centrality), may serve as targets for the development of prevention and intervention strategies. Pertaining to the last two points, psychological networks are mostly estimated in cross-sectional data and cannot draw firm conclusions on causal relations, but they can be used as exploratory hypothesis-generating structures that can point toward potential causal relations.

A few studies have applied network approaches to well-being phenotypes. In a sample of Chinese adolescents, a network model was applied to the 20-item Chinese version of the engagement, perseverance, optimism, connectedness, and happiness (EPOCH) scale. Being cheerful, being absorbed in current activities, and being optimistic were the most central components of the network, suggesting that these traits might serve as useful targets for improving well-being in adolescents (Zeng et al., 2019). In another study, fourteen well-being

items measuring affective-emotional aspects, cognitive-evaluative dimensions, and psychological functioning were used to create a network in a large UK sample (Stochl et al., 2019). Three items related to self-perception and cheerfulness were most central to the network, suggesting that these domains play an important role in influencing other aspects of well-being. These studies thus point to interesting prevention and intervention targets that can be used by (positive) psychologists or clinicians, and for examples school teachers, to improve well-being. These studies did not, however, focus on what these networks tell us about the structure of well-being as a research topic, i.e. to clarify terminology and well-being concepts. For example, by examining how items corresponding to different well-being constructs cluster together, we can learn something about how those different constructs relate to each other. One study did focus on this topic by creating a network that included measures of both SWB and PWB in an Italian adult sample (Giuntoli & Vidotto, 2021). Based on their findings, the authors conclude that the final network was most in line with Diener's definition of well-being, with life satisfaction, positive and negative experiences, and perceived positive functioning as different, but connected, well-being domains.

This study seeks to extend this work by estimating a network that does not only include different well-being measures, but also broader well-being spectrum phenotypes: depressive symptoms, neuroticism, self-rated health, and loneliness in a sample of Dutch adults. By estimating a broad well-being spectrum (WBS) network, we aim to get better insight into well-being itself in terms of how clearly delineated or interconnected different well-being items from different domains are, and the added value of network science as a method for answering questions about the nature of the well-being construct.

Method

Sample

Study participants are voluntarily registered with the Adult Netherlands Twin Register (NTR) (Ligthart et al., 2019). For the current project we made use of four waves of NTR data collection: 1) the 8th wave of data collection, collected from 2008 to 2010, 2) the 10th wave of data collection, collected from 2012 to 2014, 3) the 13th wave of data collection, collected in 2017-2018, 4) and the 14th wave of data collection, collected in 2019- February 2020. These waves were selected based on the availability of relevant well-being variables. Participants were included if they participated in at least one of these surveys. If data on multiple time-points were available, we selected the most recent time-point.

Importantly, since the NTR collects data in multiples and their family members, many individuals are genetically related to each other, meaning that the observations are not entirely independent. To prevent bias due to these dependencies, we selected two samples so that within each sample, all individuals were genetically unrelated to each other. These samples were used as a trimming sample (to check for potential redundant nodes) and an estimation sample (to estimate the network) (see Figure 1). The trimming sample included only participants that had data available for all the different traits. In total, the trimming sample included 1343 individuals (63% females, $M (SD)$ age = 53.18 (9.45)). The estimation sample included 759 participants (75% females, $M (SD)$ age = 45.27 (11.12)).

[Figure 1 near here]

Measures

To assess the well-being spectrum phenotypes the following standardized instruments were used:

The Subjective Happiness Scale (Lyubomirsky & Lepper, 1999). Four items were rated on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). An example of an item is: “On

the whole, I am a happy person". We recoded the items so that for all items, a higher score meant higher levels of happiness.

The Satisfaction with Life Scale (Diener et al., 1985). Five items were rated on a Likert scale from 1 (strongly disagree) to 7 (strongly agree). An example of an item is: *'My living conditions are excellent'*.

Cantril's ladder (Cantril, 1965) was used to assess *Quality of Life* (QoL). Participants were asked *'Where on the scale would you put your life in general?'*, with 0 representing the worst possible life and 10 representing the best possible life.

The Short Flourishing Scale (Diener et al., 2010). The scale contains 8 items that have to be rated from 1-7 using a Likert scale. 1 resembles 'strongly disagree' and 7 resembles 'strongly agree'. An example of an item is: *'I am competent and capable in the activities that are important to me'*.

Depressive symptoms. The depressive problems subscale from the adult self-report (ASR) of The Achenbach System of Empirically Based Assessment (ASEBA) was used to assess depressive symptoms (Rescorla & Achenbach, 2004). 14 items were rated from 0-2 (0= not true, 1 = somewhat true, 2= very true). An example of an item is: *'I feel worthless or inferior'*.

Loneliness. The three items from the short scale for assessing loneliness in large epidemiological studies were used to assess loneliness (Hughes et al., 2004). For each item, participants indicated how often they identify with a statement, rated as: 0=almost never, 1=sometimes, or 2=often. An example of a statement is: *'How often do you feel isolated from others?'*.

Neuroticism. The NEO-FFI neuroticism subscale was used to assess neuroticism. The subscale consists of 12 items, and each item was rated on a 5-point scale from 1 (strongly

disagree) to 5 (strongly agree. An example of an item is '*I often feel tense and jittery*'. Half of the items were reverse-coded so that a higher score indicated higher levels of neuroticism.

Self-rated health. A single item was used to evaluate self-rated health: '*How would you rate your general health?*' (Eriksson et al., 2001). This item was rated on a 5-point scale ranging from 'Bad' to 'Excellent'.

Statistical analyses

An overview of the different steps of the analysis plan is depicted in Figure 1. Below, we provide more detail on each separate step.

Item selection

Before estimating networks, we examined the distribution of all the items. We excluded ordinal variables having less than 2 observations for any of the observed response categories. The threshold value 2 was chosen because this is a requirement for the non-parametric bootstrap of ordinal items we performed (Epskamp et al. 2015) at a later stage. Items were excluded for the analyses if they did not meet this requirement.

To estimate the most parsimonious network in the estimation sample, we used the trimming sample to examine item redundancy (i.e. items that are not essential to the network since they correlate highly with other items). The goldbricker function implemented in the networktools r package (Jones and Jones 2017) was used to assess potential item redundancy. With this function, strongly correlated item pairs ($r \geq .7$) that had less than 50% unique combinations with other items (i.e. less than 50% of significantly different correlations with other nodes, $p = .05$) were identified. Next, the net_reduce function was used to choose the more unique node of each redundant pair and remove the redundant one. Based on the network trimming in the trimming sample, we estimated the network without redundant nodes in the estimation sample.

Regularized network estimation

We estimated the WBS network using the estimation sample with all items that remained after the item selection and item trimming phase. We included sex and age as covariates. The network was estimated using the *bootnet* package (Epskamp, Borsboom, et al. 2018), and visualized using the *qgraph* package (Epskamp et al. 2012) in Rstudio (RStudio Team, 2020). Since mixed variable types (continuous and ordinal) were included in the network, the function *Mixed Graphical Models (MGM)*, which allows for the inclusion of both categorical and continuous data, was chosen as the best regularized estimation method for our data (Haslbeck & Waldorp, 2015). The model employed by MGM is a pairwise Markov random field (PMRF) model, where nodes are connected by undirected edges, and unconnected nodes are independent after conditioning on all other variables. Least absolute shrinkage and selection operator (LASSO) regularization with Extended Bayesian Information Criterion (EBIC) model selection was applied to limit the number of spurious edges. The tuning parameter λ (lambda), which controls the level of sparsity (i.e. the likelihood that spurious edges are removed) was set at the default value of .5. The network was plotted using the multidimensional scaling (MDS) function implemented in the *networktools* R package. In MDS plots, the distance between the nodes is reflective of the strength of the association between two nodes, with nodes placed closer together sharing stronger associations.

Centrality and Clustering

Three commonly used centrality measures: *closeness*, *betweenness*, and *strength*, were used to provide information on the centrality of the individual nodes. *Closeness* (inverse of the sum of distances from one node to all other nodes) indicates how strongly a node is indirectly connected to other nodes. *Betweenness* is the quantification of how often one node is in the shortest paths between other nodes and therefore reflects the importance of a node in

connecting other nodes. *Strength* (the sum of absolute edge weights connected to each node) indicates how strongly a node is directly connected to other nodes. The strength centrality measure works most optimally in a network with exclusively positive edges as this index does not distinguish between positive and negative edges. We, however, expect, due to the WBS structure, positive (well-being, self-rated health) as well as negative (neuroticism, depression, loneliness) edges. Therefore, we also estimated the *expected influence* of the nodes. Expected influence assesses a node's strength but retains the positive or negative value of the edge-weights. In case of a node with both negative and positive edges, expected influence is a preferable measure over strength, as a node with a comparable number positive and negative edges might have little influence on the overall network as these influences can cancel each other out (which is not taken into account with the strength index).

In order to draw conclusions on the network as a whole, we estimated the *global clustering coefficient* and the *small-worldness* of the network. The *global clustering coefficient* (i.e. transitivity) is an estimate for how often a node's neighbouring nodes are also connected to each other (Costantini et al., 2019). It reflects the number of closed triads (groups of three nodes that are all connected to each other) over the number of possible triads, with a global clustering coefficient of 0 meaning that none of the triads are closed, and 1 meaning that every triad is closed. A network with a high global clustering coefficient is thus characterized by a highly connected and clustered network structure, while a low global clustering coefficient indicates the network is comprised of numerous weak ties. Next, we calculated the value of *small-worldness*, which allows us insight into the average clustering of the network. In a small world network, it takes a small number of steps for most nodes to reach other nodes. If a network has a small-worldness value higher than 3, the global clustering coefficient is high and the average path lengths are short (Watts & Strogatz, 1998). A value between 1 and 3 is considered a borderline value (Humphries & Gurney, 2008).

Performance

After estimating our network in the estimation sample, we examined its performance using simulations with different sample sizes. Our main aim was to find out to what extent the performance (in terms of different parameters, see below) of the network would have increased if we had estimated the network with a bigger sample size. To examine this, simulations were performed based on the estimated network structure (Sacha Epskamp, Maris, et al., 2018) using the *netSimulator* function in *bootnet*. Since simulations under LASSO regularized parameters might result in parameters being biased towards zero due to shrinkage, we first fit the model using LASSO to obtain the estimated network structure, and then refit the model with only those edges without LASSO regularization. LASSO regularization with EBIC model selection has previously been shown to have high specificity, but varying sensitivity (Epskamp et al. 2017). Data for three different sample sizes ($N=500/1000/1500$) were simulated and the three indices sensitivity, specificity, and correlation were examined. Sensitivity in this context means the true-positive rate of the edges in the network, i.e., the amount of edges present in the true network that were also in the estimated network. Specificity is the opposite of sensitivity: the true-negative rate. The correlation reveals how much the true network structure and the simulated network structures are alike. Additionally, the correlation between the centrality indices (strength, closeness, betweenness, and expected influence) of the true network and the estimated networks were estimated.

Edge-weight accuracy

Lastly, we examined how accurately we estimated the edge-weights in our network by using the non-parametric bootstrapping in *bootnet* (Epskamp, Borsboom, et al. 2018). Using this method, observations are resampled with replacement to create new plausible datasets where

the edge-weights can be re-estimated in. Based on a 1000 bootstraps, a 95% confidence interval (CI) around the edge-weights was estimated. These CIs can be used to assess accuracy of the edge-weights, with wider CIs reflecting less accurate edges.

Results

Item selection

Five items were removed because they did not meet the threshold of at least two observations in each category. The following items were removed: the self-rated health item (*“How would you rate your general health?”*), three items from the flourishing scale (*“I am engaged and interested in my daily activities”*, *“I actively contribute to the happiness and well-being of others”*, and *“People respect me”*), and one depression item (*“I deliberately try to hurt or kill myself”*).

Network trimming

Using the goldbricker function four nodes were identified that could be removed. The quality of life item (*“Where on the scale would you put your life in general?”*) was deemed redundant since it was not significantly different from a satisfaction with life item (*“I’m satisfied with my life”*) within the context of this network. Two subjective happiness scale items (*“On the whole I am a happy person”* & *“On the whole, I am very happy, I enjoy life come what may and I always make the best of things”*) were excluded because of redundancy in the context of two other subjective happiness items: *“Compared with most of my peers, I am less happy than they are”* and *“On the whole, I am not very happy, although I am not depressed I never seem to be as happy as I could be”*, respectively. Lastly, one depression item (*“I feel tired without good reason”*) had a redundant role in the network because of another depression item (*“I do not have much energy”*). After removing these items from the estimation data, 41 items (including covariates) were left for network estimation.

Network structure

The multidimensional scaling (MDS) layout of the well-being network is shown in Figure 2, where the distance between the nodes is reflective of how strongly the nodes are correlated (Jones et al., 2018). A visual inspection of this graph reveals two clusters: a depression, loneliness, and neuroticism cluster reflecting the more negative aspects of the WBS, and a cluster of the different well-being measures, reflecting the positive aspects of the WBS. Supplementary Table 1 provides the partial correlation matrix that underlies the network depicted in Figure 2 (with item descriptions in Supplementary Table 2). The positive and negative cluster are mostly connected through depression nodes connecting to different well-being nodes. While loneliness and neuroticism are also directly connected to flourishing and satisfaction with life, respectively, they are mostly indirectly connected to well-being items through depression nodes. Additionally, we see that items that belong to the same questionnaire tend to cluster together. While not immediately obvious from the graph, age was not connected to any of the variables.

[Figure 2 near here]

Centrality and Clustering

Standardized centrality indices (strength, betweenness, closeness, and expected influence) for each item are depicted in Figure 3. Lower, negative Z-scores indicate nodes with the least strength/ betweenness/closeness, while higher, positive Z-scores indicate nodes with high centrality. On all centrality indices, SWL3 (*'I am satisfied with my life'*), NEU6 (*'I sometimes feel completely worthless'*), DEP3 (*'I feel worthless or inferior'*), and DEP11 (*'I am unhappy, sad, or depressed'*) scored relatively high. Sex, which was included as a covariate, scored the lowest on each centrality index. On the whole, most items scored relatively low on betweenness, which is also reflected in the fact that most nodes reside in the

periphery of the network (see Figure 2). This indicates that most nodes do not act as a connector for other nodes. We estimated both strength and expected influence since our network contained both negative and positive nodes (which is not taken into account by the strength index). However, as a result of the fact that there were not many negative edges in the network, the results for strength and expected influence are very similar. The global clustering coefficient of the entire network was .32, and the small-worldness value was 2.44, fulfilling the criteria to be considered a small-world network.

[Figure 3 near here]

Performance

We ran three simulations with varying sample sizes ($N=500/1000/1500$) to assess the performance of the network. The results from these simulations can be found in Figure 4. Across each sample size, the correlation, betweenness, specificity, strength, and expected influence of the network remained relatively stable and high. Sensitivity (the true-positive rate of the edges), however, is rather low across all different sample sizes and drops steeply at a sample size of $N=500$ (values around .5). It is not surprising to find a very high specificity but lower sensitivity when using LASSO regularization (Epskamp et al. 2017). Given our modest sample size of $N=759$, it is possible that a substantial number of edges in the “true network” were not present in our estimated network. The closeness of the network is zero in all simulations due to the age node not being connected to the rest of the network.

[Figure 4 near here]

Accuracy

Supplementary Figure 1 contains the bootstrapped CIs of the edge-weights (edge labels were left out for readability) that were estimated to examine the edge-weight accuracy. On the y-axis are all edges in the network, and on the x-axis it shows the strength of the edge-weights,

with red dots as point estimates, the black dots the bootstrap means, and the grey area as 95% confidence intervals. Overall, we find relatively large CIs. These CIs do not reflect whether or not an edge should have been set at zero, but rather the accuracy of the estimated edge-weights, indicating that the strength of the edges should be interpreted with caution.

Discussion

In the present study, we set out to study the well-being spectrum (WBS) from a network perspective. By modeling the WBS as a set of correlated items without higher-order factors, we aimed to get better insight into the well-being construct itself, and evaluate the added value of network psychometrics for providing novel information on the well-being construct. The final network suggests two clusters, with on the one hand the “negative” spectrum items of depression, loneliness and neuroticism, and on the other hand the “positive” spectrum items from the different well-being measures.

Before estimating the network, we took two steps that led to the exclusion of several items. First, we excluded items that had less than 2 observations for any of the observed response categories in either the trimming or the estimation sample. This led to the exclusion of the self-rated health item, three flourishing items and one depression item. Next, we excluded items that could be classified as redundant nodes. When two items were strongly correlated ($r > .7$) and had less than 50% significantly different correlations with other items, the least unique item of the pair was excluded due to redundancy. This led to the exclusion of the quality of life item, two subjective happiness items and one depression item. Importantly, the exclusion of these items does not mean they are unrelated to the network, but rather that the item is redundant for this specific network because there is another item that plays a

similar role in the network. For example, one of the satisfaction with life items was highly correlated with the excluded quality of life item ($r = .73$) and additionally correlated similarly with other nodes in the network. Since this satisfaction with life item was more unique to the network than the quality of life item (in terms of its redundancy statistics with other nodes), this item was retained instead of the quality of life item. Therefore, this does not mean that Quality of Life should be disregarded with respect to well-being, but rather that it correlates similarly with the rest of the network as satisfaction with life. An interesting finding is that two subjective happiness items were excluded because they were redundant in light of two other subjective happiness items. There have been other studies showing that a three-item version of the SHS performs equally well as the 4-item version (O'Connor et al., 2015), and that removing item 4 (“Some people are not very happy. Although they are not depressed, they never seem as happy as they might be. To what extent does this characterization describe you?”) leads to higher reliability (Karakasidou et al., 2016). However, this item was actually retained for subjective happiness in the present network, likely because the item was not redundant in terms of its correlations with other items in the network, even though it might be inconsistent with the other items in terms of reliability. This specific item may thus not carry additional, unique information for the concept of subjective happiness, but it may do so for the broader concept of well-being.

After these exclusion steps, we estimated the WBS network in the estimation sample. The network (borderline) qualified as a small-world network, i.e., it has small average path distances with high clustering compared to random networks. Visual inspection of the network suggests the presence of two smaller networks, connected through a few items. One cluster consisted of positive items for subjective happiness, satisfaction with life and flourishing, while the other, more negative, cluster included depressive symptoms, neuroticism, loneliness, and sex. The positive and negative cluster were predominantly

connected by edges between multiple depression items and multiple well-being items, and not by one or two “bridge items” (see Supplementary Tables 1-2). Age was not connected to other nodes in the network, i.e., it was independent after conditioning on all other variables, indicating that the network structure is independent of the age of the participant in our adult sample with an age range from 19 to 65. The network structure of adolescent well-being in terms of EPOCH was studied in a Chinese sample by Zeng and colleagues, but not yet in relation to well-being related phenotypes like depression (Zeng et al., 2019). Interesting would be to repeat our current efforts in a sample of children/adolescents or in a sample of older adults.

With respect to the well-being items, we see that items belonging to the same measurement instrument tend to cluster together, but there are also several connections between well-being items from different instruments. On the one hand, the clustering of well-being items belonging to the same measurement instrument (i.e. flourishing, satisfaction with life, and subjective happiness) is in line with theories such as Keyes’ theory on flourishing or Diener’s theory on SWB that distinguish different well-being domains such as cognitive well-being and psychosocial well-being (Diener, 1984; Keyes, 2005). On the other hand, we also see that all well-being items are highly clustered and interconnected, suggesting that the different domains are not as clearly delineated as may be claimed by different theories, or as might be concluded from factor analytic research modeling these items as the result of correlated, but clearly distinct higher-order factors. Taken together, these results are very similar to previous findings for the WBS where we found high phenotypic and genetic correlations between WBS measures, and additionally identified a genomic factor model where positive and negative traits loaded on separate, but highly correlating factors (Baselmans et al. 2019). This is similar to findings by Giuntoli & Vidotto, who conclude based on their network analyses that different SWB and flourishing components are closely

related constructs (Giuntoli & Vidotto, 2021). In addition, it is in line with other studies emphasizing that different well-being phenotypes are highly interconnected (Kim et al., 2016; Kokko et al., 2013).

One of the advantages of network psychometry is the possibility to examine nodes in terms of different centrality indices. On all four centrality indices (strength, closeness, betweenness & expected influence), four items scored relatively well compared to all other nodes: SWL3 (*'I am satisfied with my life'*), NEU6 (*'I sometimes feel completely worthless'*), DEP3 (*'I feel worthless or inferior'*), and DEP11 (*'I am unhappy, sad, or depressed'*). This indicates that these nodes have stronger and more direct connections to other nodes in the network, and that they more often serve as shortest paths between other nodes. A potential interpretation in this regard is that the most central nodes reflect the items that are most representative of the WBS. Thus, to get a general idea of the WBS with a limited amount of items, one might benefit most from examining these items. Additionally, the four nodes that were removed due to redundancy are also interesting for follow-up analyses: these items were removed because they correlated strongly with one or more other items, indicating that they might also be central to the WBS. That is, redundant items do not contribute unique information to the network with regard to well-being when taking the other items into account, which means that they do carry substantial information common to one or more items in network.

These findings should be interpreted in the context of some limitations. For all performance measures except sensitivity, all three sample sizes resulted in acceptable or good performance. However, with respect to sensitivity, it is likely that smaller edges remained undetected with our current sample size, and with respect to accuracy we found relatively large CIs for the edge-weights. Combined, this indicates that the study could have benefitted from a larger sample size. Moreover, we found that items that belong to the same

questionnaire tend to cluster together. While this partly reflects these items successfully capturing a particular phenotype, this likely also reflects participants answering questions belonging to the same measurement instrument more similarly than questions from different instruments as these items were presented with the same response format (Weinberger et al., 2010). More specifically, while participants filling out the surveys are unaware of which items belong to which questionnaire, the response format (e.g. scale, wording) of the different questionnaires is not always the same, potentially leading to clustering. Lastly, we were limited by the well-being items that were previously collected in our sample. For example, we did not include Ryff's different scales or items corresponding to Keyes' social well-being domain. For future research, it would be interesting to estimate an even broader well-being network that includes items on these different theories.

To conclude, the results described in this study support previous research on the WBS that links different well-being measures to depression, neuroticism, and loneliness where two highly interconnected positive and negative clusters were identified (Baselmans et al. 2019). The results further suggest that these sides are even more connected than previously hypothesized given the small-worldness of the total network. Additionally, we identify four nodes most central to the network: one satisfaction with life item, one neuroticism item, and two depression items. This suggests that to get a general sense of the WBS, these items would serve as the most informative items to evaluate. In conclusion, taking a network perspective on the well-being spectrum re-affirms prior research that demonstrates the complex interconnectivity of different well-being (related) phenotypes and rejects the view of clearly delineated well-being domains. To develop a more complete picture of well-being, including hedonic and eudaimonic aspects in a network context, additional studies are needed that include more well-being measures that measure these different aspects of well-being.

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Informed consent: Written informed consent was obtained from all individual participants included in the study.

Data availability: The Netherlands Twin Register cohort data may be accessed through the Netherlands Twin Register repository (ntr.fgb@vu.nl) upon approval of the data access committee.

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Figures

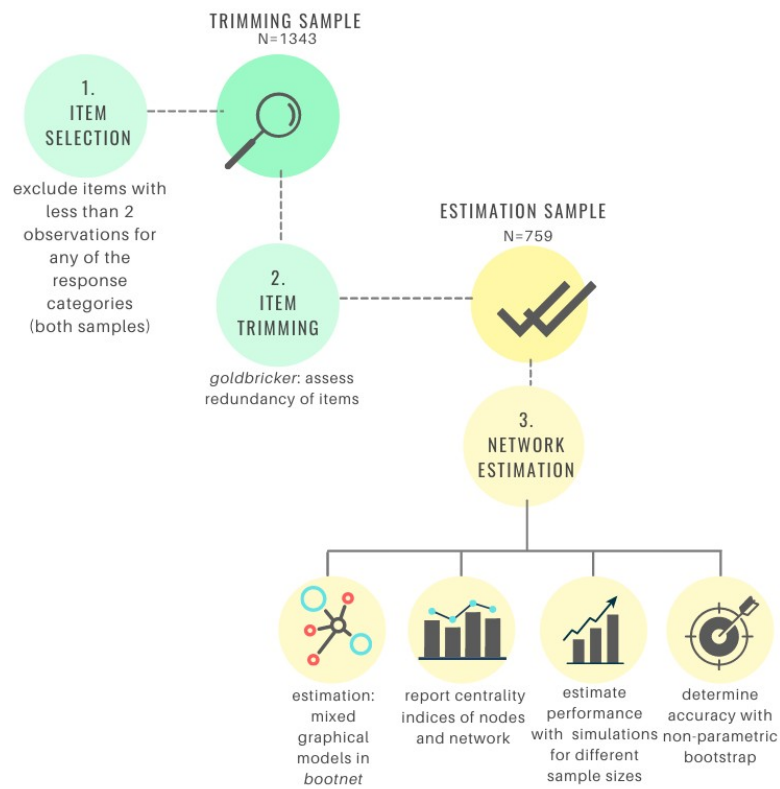
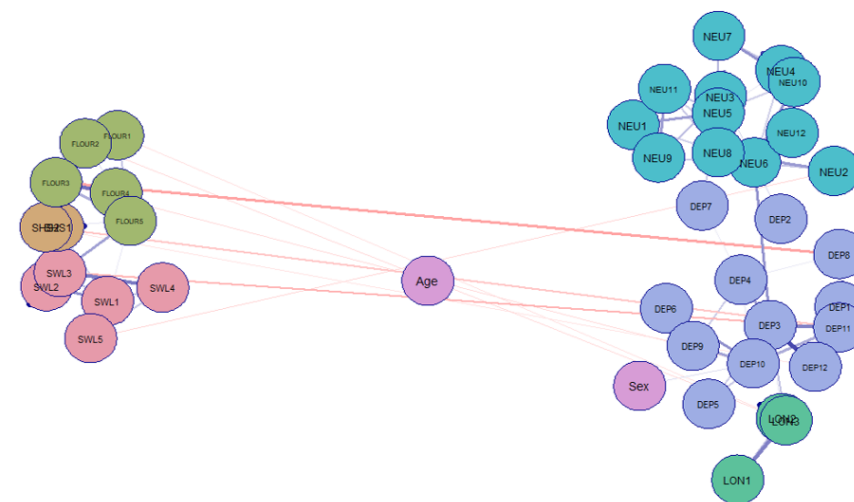


Figure 1.



Satisfaction with life	Depressive symptoms	Loneliness
<ol style="list-style-type: none"> 1. My life is going more or less as I wished. 2. My living conditions are excellent. 3. I'm satisfied with my life. 4. Until now I've always gotten the most important things I wanted in life. 5. If I had to live my life again, I would do more or less the same. 	<ol style="list-style-type: none"> 1. I cry a lot 2. I do not eat as well as I should 3. I feel worthless or inferior 4. I feel very guilty. 5. There is very little that I enjoy 6. I sleep more than most other people during day and/or night 7. I have trouble making decisions 8. I think about killing myself 9. I have trouble sleeping 10. I do not have much energy 11. I am unhappy, sad, or depressed 12. I feel that I cannot succeed 	<ol style="list-style-type: none"> 1. How often do you feel that you lack companionship? 2. How often do you feel left out? 3. How often do you feel isolated from others?
Subjective happiness	Covariates	Neuroticism
<ol style="list-style-type: none"> 1. Compared with most of my peers, I am less happy than they are (RV). 2. On the whole, I am not very happy, although I am not depressed I never seem to be as happy as I could be (RV). 	<ol style="list-style-type: none"> 1. Age 2. Sex 	<ol style="list-style-type: none"> 1. I am not a worrier (RV). 2. I often feel inferior to others. 3. When I am under a great deal of stress, I sometimes feel like I am going to pieces. 4. I rarely feel lonely or blue (RV). 5. I often feel tense and jittery. 6. I sometimes feel completely worthless. 7. I rarely feel fearful or anxious (RV). 8. I often get angry at the way people treat me. 9. Too often, when things go wrong, I get discouraged and feel like giving up. 10. I am seldom sad or depressed (RV). 11. I often feel helpless and want someone else to solve my problems. 12. At times I am so ashamed I just want to hide.
Flourishing		
<ol style="list-style-type: none"> 1. I lead a purposeful and meaningful life. 2. My social relationships are supportive and rewarding. 3. I am competent and capable in the activities that are important to me. 4. I am a good person and live a good life. 5. I am optimistic about my future. 		

Figure 2.

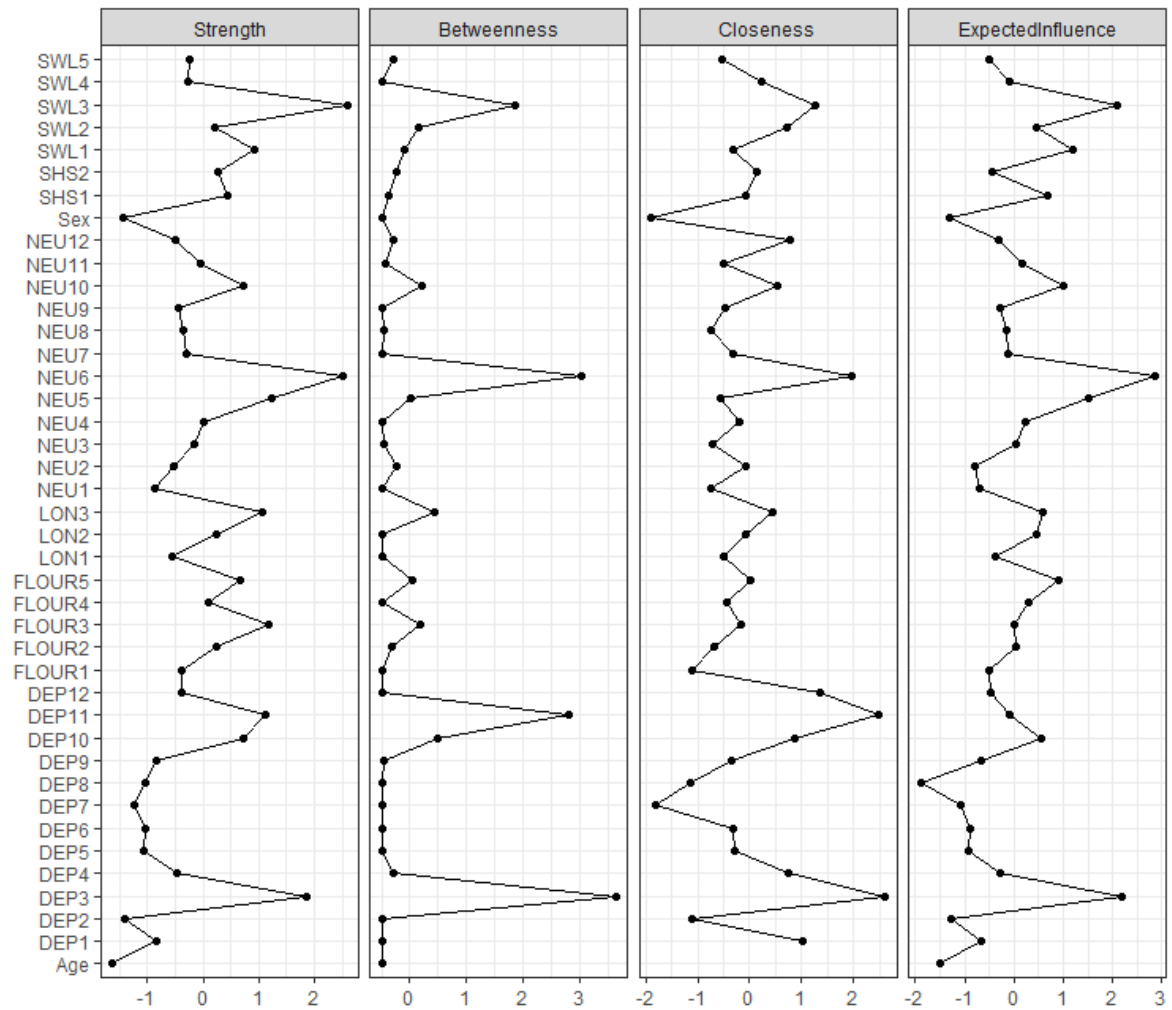


Figure 3.

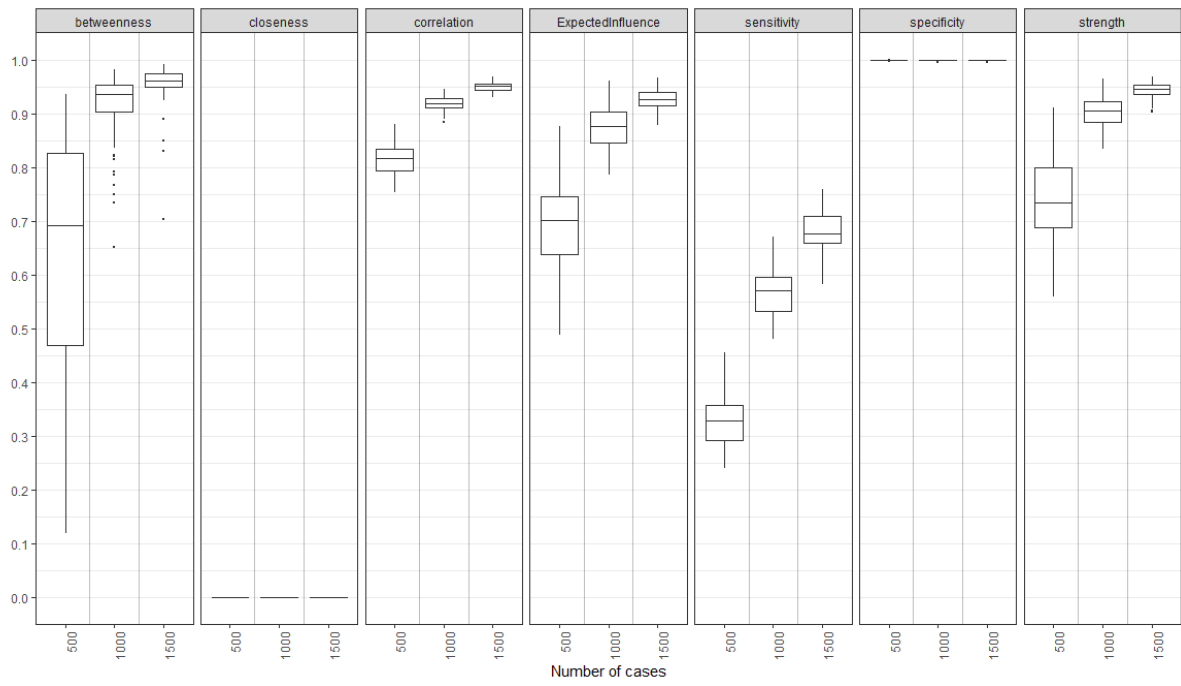


Figure 4.

Figure Captions

Fig 1. Overview of the analysis plan.

Fig 2. Multidimensional scaling layout network of the well-being spectrum. Blue lines indicate positive associations, red lines indicate negative associations. RV= reverse coded before the analyses.

Fig 3. Centrality indices of all nodes (see Figure 2 for item descriptions).

Fig 4. Results from the simulations for three different sample sizes.